Federated Learning for Anomaly Detection in Industrial Internet of Things (IIoT) Networks: Balancing Security and Privacy

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(2025)

Abstract

This research thesis introduced a novel structure that influence on federated learning for anomaly detection in industrial internet of things (IIOT) networks. It is designed to pinpoint cyber security threats in industrial environments. The structure apply differential privacy technique and federated learning technique to train a global anomaly detection model short of yielding individual devices data privacy. The methodology relates to a multi-step process beginning with data collection from multiple IIOT devices. This research introduced Edge-IIoTset dataset that facilitate the training and perception of machine learning based intrusion detection system through centralized and federated learning paradigms. It is organized into seven layers: Cloud Computing Layer, Network Functions Virtualization Layer, Blockchain Network Layer, Fog Computing Layer, Software-Defined Networking Layer, Edge Computing Layer, and IoT/IIoT Perception Layer. More than 10 types of IoT devices are used to generate data. A total of 1176 features were extracted, with 61 high-correlation features selected for analysis. The full dataset contains 20.9 million records, including 11.2 million normal and 9.7 million attack records. Preprocessed ML and DL-ready files with 2.3 million records are provided for easy model training. Preprocessing of raw data is included in methodology to applying techniques such as feature scaling and imputations. A thorough check for missing values is conducted using imputation techniques. No missing values were found in the dataset. Label encoding is used to convert categorical values like `Attack_Type` into numerical values from 0 to 14. Z-score normalization is applied to ensure all features are on the same scale, improving learning efficiency. Each feature value is standardized using its local mean and standard deviation to create scaled feature values. The dataset is split into 70% training, 15% validation, and 15% test sets. The dataset is distributed among 15 clients. Each client receives approximately 221 K samples, with slight variations due to rounding. The data is non-IID (non-independent and identically distributed), meaning each client may encounter different distributions of attack types—for example, one client might primarily see DDoS traffic. First IIoT devices create their local models using LSTM technique in local model training to get temporal data reliance. Each IIoT device trains a 3-layer LSTM model locally to capture temporal dependencies in traffic behavior using time-series data. The model is trained using a fixed learning rate (0.01) and a gradient clipping that helps it correctly sort traffic into different categories. IIoT devices integrates to train a global anomaly detection model in federated learning setup phase to maintaining data privacy through technique like federated Averaging. FedAvg stacks client model weights and

averages them to produce an aggregated model. After averaging, Gaussian noise (0.01) is added to the weights for privacy protection. The updated global model is then redistributed to all clients for the next round. The federated learning process runs over 10 global rounds of model updating. After each round, the global model is evaluated on a validation dataset. Validation loss is computed to monitor convergence and detect overfitting. The process allows learning from distributed clients without compromising privacy. Final model performance reflects the aggregated knowledge from all client data. Global model evaluation captures the model performances through metrices such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC. Privacy and security analysis determine federated learning security significances using differential privacy technique to save sensitive data. The Federated LSTM stands out as the optimal choice, balancing high accuracy, low error rates, and efficient training. While MLP and Feedforward NN are strong alternatives, their computational overhead and marginally lower performance make them less ideal. Traditional models (Logistic Regression, SGD) offer faster training but lack the precision required for critical IoT security tasks. Continuous monitoring should prioritize the Federated LSTM for real-time threat detection, with periodic validation against MLP to ensure consistency. Models like GNG and Ridge Classifier should be deprecated due to their poor performance. The deployment phase merged the global trained model onto IIoT devices to supporting real time anomaly detection and refining industrial system flexibility. Continuous monitoring and improvement improve the model performance and operational capability. The proposed method gives a optimistic solution to balance security and privacy, and enhance resilience against potential threats in IIoT networks.

Table of Contents

List of Tables

List of Figures

List of Equations

Chapter 1: Introduction

This chapter give the basic idea of Industrial Internet of Things (IIoT) with the concept of federated learning tactics usage in IIoT. In this chapter the detail information clear that what is Industrial Internet of Thing (IIoT) and how we can apply and use federated learnings techniques in IIoT Networking to get the execution of these methods and can make system more reliable and efficient.

1.1 Introduction

The Internet of Things (IIoT) manifests to uprising in industrial operations where authentic production and production processes are progressive by connecting sensors, mechanisms and smart measures. The confluence of physical and digital realm has conducted to exceptional levels of efficiency, optimizations and tracking time in industries. From portending conservations in assembling facilitates to exceptional project management in the industrial industry. The internet of things is adapting how organization observe and engage with their workplace by utilizing the huge amount of data formed by automation and systems. The (IIoT) must turn out more efficient, reduce time and increase comprehensive advisability. Even so these ascents bring with them effects such as cyber security threats middleware issues and data privacy apprehensions. This demands a strong base and strategy to expand the benefits of IIoT while moderation the associated risk. In the globe of IIoT data is a key resource that urge efficiency, innovation and decision making. Information amass from different source into IIoT systems gives remarkable openings to pick up important data. But this sum of information brings with it enormous impacts: how to pick up judgment skills whereas maintaining the security and privacy of touchy information. To guarantee the unwavering quality and security of IIoT frameworks peculiarity discoveries acts primary affect by identifying contrasts in circumstances that will presage malevolent action. Indeed so a adjust between security and protection consideration requests a fruitful inconsistency location in industrial IOT systems. Federated learning shows up as hopeful arrangement for these issues by giving choices making zones for preparing models hubs of gadgets or frameworks. Dissimilar solidified frameworks utilize machine learning models who are prepared locally on a gadget through combined learning, only overhauls are collected from worldwide demonstrate. The show not as it were secure effectiveness of unique information but it moreover minimizing the dangers of information spilling and unauthorized get to. In IIoT FL gives unused approaches to preserve and upgrade security and protection whereas authenticating others irregularity discovery. Without gambling the security and

protection of information FL makes a difference to builds more capable inconsistency discovery models. The (IIoT) has guided in a time of alter over diverse businesses by expanding operational productivity by interfacing associated gadgets that collect and share data. This association empowers proficiency, robotization and quick decision-making in mechanical situations. But the comprehensive blending of Industrial IoT gadgets has moreover lifted concerns around cybersecurity, as these systems ended up targets of cyberattacks and information spillage. To lighten these issues, peculiarity location turns an imperative security component. This handle relates finding deviations from the nearness of the framework, that takes after the discoveries of assaults and irregularity. By applying irregularity discovery businesses can make their IIoT systems more flexibility, Assuring that their operations stay dependable and secure within the confront of changing cyber dangers. FL show decentralized machine learning (ML) technology who supports collaborative learning without the need to directly prepare hardware. In anomaly detection in IIoT systems, (FL) endeavors by giving each IIoT device that train a local model through its data. Sending data to the central server (which raises privacy concerns), only the updated models (like gradients or weights) are shared with the devices. This decentralized method has many advantages. First, it reduces the privacy risks related with sharing raw data, as only the data shows a slightly updated pattern. This Certain that important industrial information is preserved safe through all devices. Second, (FL) does not need central storage to store and process data, that reducing the risk of system disaster. (FL) increases the overall vigorous of the sensing system by dispensation the computation across multiple devices. Additionally, (FL) enables Incessant learning and updating without yielding data privacy, as each IIoT device can update its local model based on data changes. Overall, (FL) show optimistic way to apply security and privacy supervision anomaly in the IIoT environment and addresses fundamental risks associated to data privacy and system flexibility. Conventional anomaly detection methods normally use a centralized approach that collects information from all network connections. Components are combined and processed on the global server. This approach has many advantages, including centralized management of data analysis and greater efficiency due to the convenient of large computer resources. But it still elevates meaningful privacy concerns. Raw sensor data from IIoT devices often contains sensitive industrial and organizational data that must be send on a global basis for analysis. This hoists issues around information protection and security, as the engendering and capacity of touchy information can be focused on by aggressors. It too makes independent

engineering disappointment. Any harm or interference to the worldwide server can cause framework calamity and take off the whole IIoT arrange helpless. The helpless in this case highlight the significance of finding elective ways to distinguish delicacy that categorize individual information mid-design and separate control to reduce the dangers related with them. Empowered by the hypothesis of the combined preparing goes to as an approach for collecting recognition from the dispersed information without concurrently yielding the mystery or keenness of the data. Like a trusted specialists that interfaces and proliferate security data, unified preparing can uncover valuable decide designs whereas ensuring the security and security of IIoT information. By offer assistance of this research consumption, we point to supply the change of inconsistency location within the IIoT environment, driving to more secure, private capture and record of important information. By partner the contrast among security, security, and irregularity discovery, we point to raise the approval of unified preparing as a sensible way to progress the obtainability capacity and Fidelity of mechanical IoT networks against chance and concern. Highlight scaling is an imperative preprocessing step for inconsistency location in FL because it normalizes the highlight extend to a uniform scale. In an mechanical IoT arrange, where sensors can deliver information of distinctive sizes, parameterization guarantees that each highlight contributes similarly to the preparing show. Include scaling coordinate with the (FL) calculation that amass speedier by standardizing the information and diminish the chance of upgrading the deluding show due to large-scale highlights success the run. Moreover, highlight scaling can offer assistance upgrade the execution of irregularity location models by diminish the affectability of special case and clamor within the information, hence making it completely utilized in numerous work environments. Fragmented information that act as challenge in Mechanical IoT systems Ascription strategies play an critical part in taking care of due to sensor disappointment, communication mistakes, or illicit information approval. In FL peculiarity discovery framework, addition strategies such as cruel ascription, middle ascription, or advanced methods such as K-nearest neighbor (KNN) introduction can adjust imperative lost components without yielding delicate data. Ascription verify that the FL show is completely prepared and speaks to the dataset by filling in lost focuses, hence growing its exactness in identifying irregularities and lessening negative result. Besides, insertion innovation makes a difference growing the adaptability of FL frameworks by diminishing the impact of lost information on show execution, in this manner expanding the unwavering quality of peculiarity discovery in a energetic IIoT supportability. In IIoT systems inconsistency discovery

can be done through (FedAvg) and secure multiparty computing (SMC) procedures that bolster the execution and security of federated learning. Federated averaging permits devices to facilitate worldwide design location by averaging neighborhood design overhauls whereas putting away crude information decentralized. This approach secure information security additionally help particular of IIoT information sources to create a vigorous show. SMC, then again canimmovably compute total outline without uncovering partitioned help, hence sparing delicate information from unauthorized get to. Acknowledgment to the blending of Federated Averaging (FedAvg) and secure multiparty computing (SMC) FL can identify irregularity in IIoT zones, Confirm information mystery and show integrity relatively. Actualizing long short term memory (LSTM) calculations in FL structure improve the productivity of inconsistency discovery in IIoT systems by making worldly parameters and energetic designs in sensor information. Both long short term memory (LSTM) calculations and support vector machine (SVM) models are viable at modeling successive information and picking up the forms in mechanical forms. In sensor information long short term memory (LSTM) calculations are configured to pick up worldly parameters and on the other hand support vector machine (SVM) overhaul worldwide parameters by getting parameters from neighborhood show parameters. To begin with long short term memory (LSTM) calculations make nearby transient parameters at that point SVM model total these parameters to build a well structure worldwide demonstrate. Nearby prepared demonstrate coordinates utilizing LSTM and (SVM) to make a worldwide demonstrate in Model aggregation. Worldwide show assessment captures the show exhibitions through metrices such as Accuracy, Precision, Review, F1-Score, and ROC-AUC. Protection and security investigation decide FL security significances utilizing differential security and encryption methods to spare touchy information. The deployment stage combine the worldwide prepared demonstrate onto IIoT gadgets to supporting genuine time inconsistency location and refining industrial framework adaptability. This term paper points to look at the request of FL for peculiarity discovery in mechanical IoT systems, centering on security measures and protection angles. To protect information security and protection in mechanical time able to recognizing security vulnerability by examination and testing the adequacy of the federated learning. Encourage we aim to explore different challenges and availabilities that relates to FL inconsistency location within the worldwide IIoT environment. This term paper will take an in-depth see at the application of (FL) for irregularity discovery in (IIoT) systems to completely get it its preferences and drawbacks. In this term paper we'll examine distinctive suit able FL, security

and security related techniques which adjust emphatically between discovery peculiarity and ensuring information in (IIoT). Uncover the complication of the IIoT environment, with a constrained get to of gadgets, non-IDID (free identifiers) sending, and affiliation. This term paper will display a arrangement to illuminate these issues, counting the one of a kind highlights of IIoT Structure.

1.2 Categories of Federated Learning

Federated Learning (FL) may be a disseminated machine learning method who allow numerous decentralized substances to collaboratively prepare a worldwide demonstrate whereas keeping their information neighborhood. This strategy makes a difference control protection trepidation and information security adversity by attest that information does not have to be be substituted between collaborator. There are a few key categories of FL, each suitable to diverse settings and needs.

1.2.1 Horizontal Federated Learning

HFL moreover known as Cross-Silo FL, relates to clients that keep information with the indistinguishable highlight space but different outlines or clients. In this case, each client might have information relating to diverse people, but the information sorts and highlights are constant against all clients. For illustration, different clinics might participate to progress a restorative determination show, each give persistent information from their claim organization. This approach is valuable when organizations need to pool their information to make strides demonstrate execution whereas keeping the information localized.

1.2.2 Vertical Federated Learning

Vertical FL or Cross-Device FL, works with cases where each client holds information with diverse highlights but for the same set of outlines. Here, clients may give common pieces of data almost the same people. For occurrence, one budgetary organization might allow count data almost clients, whereas another gives buy history. This sort of FL is agent when combined parts have particular however related information sets that ought to be joined to make a more broad show.

1.2.3 Federated Transfer Learning

FTL is useable when clients have information from distinctive areas or highlight spaces, and exchange learning procedures are utilized to alter models against these ranges. This category is

uncommonly profitable when information from diverse inputs are not straightforwardly parallel but are related in a few way. For illustration, a show prepared on therapeutic information in one domain may well be change to work with information from substitute field with distinctive restorative hones or phases.

1.2.4 Federated Semi-Supervised Learning

Federated Semi-Supervised Learning acclimatize both labeled and unlabeled information from the consumer. In this approach, clients utilize their labeled information to prepare the show and the unlabeled information to progress concept. This strategy is accommodating in stages where get labeled information is soak or labor-intensive, whereas unlabeled information is more readily accessible. It permits the demonstrate to specialist the endless sum of unlabeled information to make strides learning and performance.

1.2.5 Hierarchical Federated Learning

HFL embroils different levels of FL, where neighborhood FL emerge at lower levels, and the combined comes about are sent to higher levels for more handling. This various leveled approach is accommodating in large-scale unified systems with territorial or organizational assortments, empowering productive combination and preparing of show upgrades over distinctive layers.

1.2.6 Asynchronous Federated Learning

Asynchronous Federated Learning permit consumer to update the global model separately without requiring real-time synchronization. This flexibility is important in environments with continual connectivity or where clients operate at different times or frequencies. Asynchronous updates help hold alterations in client accessibility and network requirements, making the federated learning process more reliable and acceptable.

1.2.7 Secure and Privacy Preserving Federated Learning

Security and Privacy Federated learning focuses on ensuring the security and privacy of data used in training. Multi-party computation (MPC), homomorphic encryption, differential privacy, and other technologies are used to protect the security of data and update the model. These resources are especially important in environments where sensitive information, such as medical or financial, is involved and privacy is difficult to maintain.

1.3 Working of Federated Learning

Federated Learning (FL) is an inventive machine learning approach outlined to empower agreeable show preparing over numerous decentralized gadgets or servers whereas certifying that information remains localized. The method begins with the central server build up a worldwide show and conveying its most punctual parameters to all included gadgets or clients. Each gadget at that point trains this worldwide demonstrate utilizing its claim neighborhood information. Imperatively, the information never frond the gadget; as it were the demonstrate updates such as slopes or parameter changes are send to the central server back. Once gadgets have completed their nearby preparing, they pass on their computed upgrades to the central server. The server at that point combined these overhauls to move forward the worldwide show. This joining is ordinarily speak to utilizing strategies like averaging or weighted averaging to connect commitments from diverse gadgets into a single upgraded show. The overhauled worldwide show is along these lines sent back to the gadgets, and the method of neighborhood preparing, upgrading, and combination is rehashed persistent. This persistent prepare run until the show accomplishes not too bad performance or gather to a steady state. One benefits of FL is the fitness to preserve information protection. Since the neighborhood information rest on the gadget and as it were demonstrate upgrades are shared, the hazard of information breaches and security instability is considerably diminished. Moreover, FL can minimize suspension by misusing the computational control of person gadgets, minimizing the require for consistent communication with the central server. It too scales proficient to hold a huge number of gadgets, making it fitting for applications with expansive sums of conveyed data. However, FL moreover faces various challenges. Communication effectiveness can be a clog, as visit upgrades and combination require critical transfer speed and can present suspension. The heterogeneity of information over gadgets, frequently non-IID (autonomous and indistinguishably dispersed), complicates the combination of modernize and can affect the model's capacity. Besides, the changing computational capabilities of gadgets can issue the preparing handle and the complete execution of the show.

1.4 Problem Statement

The problem of effectively detecting anomalies in Industrial Internet of Things (IIoT) networks using federated learning is critical because it directly impacts the security and privacy of industrial operations. In the context of IIoT, where devices are interconnected to optimize and automate industrial processes, undetected anomalies can lead to significant disruptions, financial losses, and

safety hazards. “The critical challenge is to develop anomaly detection techniques within federated learning frameworks that can overcome data imbalance and heterogeneity, ensuring the global model remains sensitive to anomalies while avoiding biases introduced by skewed local data distributions”.

1.5 Research Questions

- How can federated learning consolidate anomaly detection in IIoT networks while securing data privacy?
- What design deliberations are required for a cooperative learning structure in IIoT anomaly detection, pointing privacy and regulatory concernment?
- How can a federated learning structure optimize security, privacy, and efficiency in IIoT anomaly detection throughout resource constraints?
- What are the execution advantages of the proposed federated learning structure related to centralized approaches in IIoT anomaly detection?

1.6 Research Objective

- To design and implement a federated learning (FL) model to detect and classify cyber threats in IIoT environments while preserving data privacy.
- To utilize LSTM-based neural networks for handling sequential network traffic data effectively.
- To leveraging FL for training models on decentralized edge devices without sharing raw data, ensuring compliance with data privacy regulations.
- To address the challenges posed by data heterogeneity across IIoT devices in federated learning setups.

Chapter 2: Literature Review

The chapter on literature review thoroughly examines federated learning methods used in machine learning and network security. Research gaps and current research trends mentioned in this study will provide future studies on the regularization and optimization of machine learning models. In literature review we explore different related researches and give a review of given techniques and methods in a brief detail. Also mentioned how FL and (IIoT) integrated in different environment.

2.1 Summary of chapter

In this chapter, different approaches to improving privacy, security, and efficiency in industrial environments are explored, with a central point on federated learning, secure computing, and anomaly detection. The exploration reviewed inspect the unification of FL with diverse approaches, Like edge computing, blockchain, and differential privacy, to pinpoint diverse challenges like privacy of data, scalability, and robustness against attacks. Through different applications, including predictive maintenance, smart buildings, IoT networks, and intrusion detection systems, these processes establish the efficiency of FL in maintain the privacy of data while enhance model accuracy and efficiency against industrial systems. The chapter combine these researches to highlight the expertise of FL and secure computing in different domains, highlighting the priority of privacy preserving approaches in modern industrial environments.

2.2 Background Discussion

In this chapter, the writing audit excavates into the vital examination of FL, secure computing, and irregularity discovery, concentrating on how these innovations are connected over diverse zones such as IoT systems, fabricating, savvy buildings, and cybersecurity. The chapter comprehensively assess diverse inquire about papers to supply a broad translate of how FL and related innovations are expounding to address protection, security, adaptability, and proficiency challenges. The to begin with range of considers includes the advance of combined secure computing systems, as pointed within the writing. This tradition centers on how FL can successfully isolated mechanical rationale from cryptographic conventions, guaranteeing information security whereas encouraging secure computing against disseminated frameworks. By utilizing a client-server design, where each information proprietor handle their claim server, these frameworks permit for privacy-preserving computations that secure touchy data. The assessment here highlights the scalability and productivity of these frameworks, separately within the setting of IoT devices and bigger

systems, setting up their potential as open-source arrangements that can be for the most part grasped against distinctive industries. Moving on, the chapter test the application of FL in determining support (PdM) and peculiarity discovery inside the fabricating division. The center is on how FL models, especially those utilize profound learning structure like 1DCNN-BiLSTM, can be adjust to handle conveyed information situations. This portion of the chapter highlights the significance of securing information security whereas still empowering the strong preparing of machine learning models on neighborhood client information, which is at that point combined at a worldwide level. The inquire about appear how FL can refine the unwavering quality and proficiency of PdM frameworks by giving precise inconsistency location in real-time, which is significant for minimizing operational downtime and moving forward generation productivity in mechanical settings. Another critical region of research is the combination of FL with edge computing and blockchain innovation. This combination is examine as a implies to make secure and effective FL systems that can work against isolated systems without the have to be give touchy information. The chapter clarify how edge servers are utilized for neighborhood demonstrate preparing in (MEC) zones, whereas blockchain innovation affirm the security and security of show overhauls. This inquire about is for the most part important for indicating the security, security, and versatility challenges that are natural in conveyed machine learning areas, particularly those including IoT gadgets. The chapter too investigate the utilize of FL for inconsistency discovery in shrewd buildings, in which IoT sensor information is impact to prepare ML models. The center here is on how FL endure for the determined and productive location of irregularities whereas securing information protection by keeping the preparing information neighborhood to each sensor. This inquire about underscores the significance of multi-task learning in keen zones, where each sensor or gadget handle as a people assignment, offer to a worldwide show that can precisely screen and control distinctive building frameworks such as lighting, HVAC, and security. Finally, the chapter assess the development of lightweight, semi-supervised interruption discovery frameworks (IDS) for IoT gadgets, concentrating on how FL and adjustedK-means clustering can be utilized for real-time inconsistencies discovery. This investigate educate the challenges of protecting location exactness and information protection whereas decreasing vitality weariness in conveyed IoT situations.

2.3 Review of Research Papers

In [1] the author developed a Federated secure computing system outlines the pain points, design goals, architecture, client-server topology, server-side stack, client-side stack, and benchmarks dataset. To separate business logic from cryptographic protocols and ensure privacy by separating data flows up to cryptography layer are arrives the pain points are used in this research. To attest privacy by separating business logic from cryptographic operations this is accomplish by through a client-server structure in which every owner of data sprints their own server. To assure privacy-preserving computing a Federated Secure Computing technique pretend as an interface between client-side logic and server-side cryptography. The client-side load identifies lean client design, bolstering multiple programming languages and securing API relation. The server-side shows registry, discovery mechanism, and bus that support management of microservices by assure the security of API interactions and dynamic object portrait. Benchmarks show that the structure work efficiently to diverse hardware configuration. Essential, the procedure is lightweight and scalable for both internet-of-things (IoT) devices and larger networks. Federated Secure Computing is assigned as an open-source solution, consider to make privacy preserving computation available for a large range of organizations and industries. And the research is open source for both public and private sectors for more development in this era.

In [2], the author explores a federated learning approach to predictive maintenance (PdM) and anomaly detection within manufacturing area. Contribution of author is develop a effective PdM model to ensure reliability, production and efficiency while reducing anomaly. In research the author used 1DCNN-BiLSTM model for distributed data environments, and controlling time series data from IoT devices. The FL structure points data privacy by permission to local clients to train ML models on their own data, and the updates that are combined at global server. The overall structure is combined with three components: clients, groups and cloud-based server. Every client get data and train its local model using LSTM networks and send parameters updates to the groups. Groups collect all updates parameters and send it on cloud server. Cloud based server gather these parameters on global based to accurate the performance of model. The results show into these into 'NORMAL', 'BROKEN', and 'RECOVERING' states. The research show that federated learning in time series data can work more efficient and reliable anomaly detection using the model.

In [3] the author creates a secure and efficient Federated Learning (FL) network structure that join both edge computing and blockchain technology to simplify machine learning model against different independent networks without passing sensitive data. Learning Node (LN) manage each autonomous network that integrate with model training using Edge Servers (ES) in Mobile Edge Computing (MEC) environments. With the heil oh devices local model are train by computational power of Edge Servers (ES). The author combined Certificate Authority (CA) to give unique certificates for network components like LNs, gateways, and users, to reminding the security of authentication processes. Off-chain storage processes apply to control large model files efficiently. A block chain network act as a controller that control all pointer and P2P networks that make peers of all unique Edge Servers (ES). The block chain assist mechanisms to combine local models to global models, which include all local updates and apply them to global model Off-chain, while the block chain remember all updates structure. Experimental results using the Stanford Cars dataset justify the capability of the structure. Furthermore, related work punctuate the importance of blockchain in securing IoT environment and proposes a channel-based access control policy. According to this approach the author points challenges in machine learning environments, such as privacy, security, and scalability.

In [4] the author proposed a novel technique in smart building for anomaly detection using a FL (LSTM) model that influence IoT sensor data. The method utilize federated learning to maintain privacy while efficiently train machine learning models around all different sensors in a smart building. Each sensor train local model, instead of sharing the data with a central server it update local LSTM model. These local models create temporal parameters through data using LSTM, those are pivotal for detecting anomalies. The system works in multi task learning where every device is reviewed as distinguish tasks, gives to continuous learning around different sensors like who control lighting, HVAC, and security systems. The training of model consists three main stages: local training, cloud aggregation, and anomaly detection. In the phase of local training, every device process its data by considering noise and missing values. These local train model then send it parameters to glob where they are combined to create a global model. This federated LSTM structure is run against real-world datasets, to elevate performance and faster comparison of global model, thereby showcasing its potential for efficient anomaly detection in smart buildings.

In [5] the author proposed FREDY model, a novel federated learning structure that point privacy apprehension in machine learning. FREDY is intended to secure privacy while exploiting FL and DP. In the research teacher models are trained separately on their private data, and then these models inclusively make patterns on public data. These patterns are joined with noise to show privacy, and noisy combined results are used to train student models. These student models are publicly available but not for the teacher models. In federated learning environment these teacher models are trained where teacher model used its private data. In these processes the global model is send and update using Stochastic Gradient Descent (SGD). Then these teacher model make patterns on public unlabeled data. The student model are trained on this labeled public data. This method helped to protect attacks like membership inference, where attacker try to infer if the special data is used in processes. For perception, FREDY is tested using standard datasets like CIFAR-10 and MNIST, segregating its performance to models trained without privacy calibrate. Overall, FREDY gives an efficient method for privacy preserving FL, giving solution in field like healthcare, finance, and smart cities with controlling the trade-offs in privacy and automation efficiency.

In [6] the author developed a novel distributed structure for creating global behavioral fingerprints of IoT objects. This structure points challenges in IoT environments, such as privacy, scalability, and the limitations of conventional (ML) algorithms. The provided model for solution focuses on attest robustness against various potential attacks. The attack model ensure that an attacker cannot access the maximum numbers of nodes or gain information from direct device access. By using federated learning, the author improved the accuracy of model while preserving privacy through Homomorphic Encryption (HE) and Blockchain technology. For Federated Learning (SP.1), the model use function to control worker nodes and to check the behavior. For SMC strategy attacks (SP.2), identifiers are created by different place to prevent cryptographic attacks. For blockchain attacks (SP.3), it depends on existing secure blockchain solutions, and did not expand their functionality. For reputation model attacks (SP.4), they use valuable score and do not repeat anything. For IoT network attacks (SP.5), the approach it use restorative for Denial of Service (DoS) and Sleep Deprivation Attacks (SDA), ensuring that abnormal behaviors are detected and alleviate. The author represents a consequential advancement in the field, giving a countable and secure method for anomaly detection in modern IoT networks.

In [7] the author provide federated learning in methodology to consolidate intrusion detection systems (IDS) by managing data privacy. The structure included two primary approaches: horizontal and vertical FL. The working of horizontal federated learning on multiple clients owning similar features but different data samples. Organization with similar parameters combined to build a global model without providing raw data. Every node locally develops its model and sends updated parameters to a central server, which combine these updates to build a global model, by managing intrusion detection model accuracy and securing data privacy. Vertical federated learning, allows clients with individual features but Corresponding data samples. From different sources data is combined to train a global model. Clients swap model parameters except raw data, enhancing the model's accuracy and attest data privacy. This research show that federated learning techniques like federated averaging, in which model updates are joined to form a global model, and secure aggregation, which uses cryptographic methods to protect local updates during combining. To select data strategy are difficult for federated learning setup including random, stratified, proactive, and dynamic selection methods. The anomaly detection system used autoencoders which are trained on normal network traffic to search anomalies through reconstruction mistakes. NSL-KDD dataset is used in the testing phase. This method shows an excellent advancement in privacy-preserving IDS solutions in different fields.

In [8] the author give a Teaching–Learning-Based Optimization (TLBO) algorithm to design an (IDS) for IoT networks. To reduce the system and communication overhead the focus of research is to improve the detection of different cyberattacks. The research started with data collection and preprocessing steps in which they use the UNSW-NB15 dataset, which encompasses 42 features divided into subtypes such as flow, time, and content. The TLBO-IDS model is trained using the Random Forest (RF) algorithm, which is known for its vigorous classification capabilities. TLBO-IDS detects analysis, fuzzing, shellcode, worms, (DoS), exploits, and backdoor intrusion attacks. The performances of TLBO-IDS is measured using metrics such as detection rate, accuracy, throughput, and overheads. These result give TLBO-IDS outperforms existing algorithms like the bat algorithm and Genetic Algorithm (GA) in terms of detection accuracy and efficiency. The research points that TLBO-IDS's has ability to handle intrusion detection with in low device and connection overhead. The presented method showed a Consequential advancement in securing IoT networks, essential for both domestic and industrial sectors where data security is cardinal.

In [9] the creator utilized three (IoT) datasets: Modbus and Climate datasets from the TON_IoT collection, and the Disseminated Savvy Space Coordination Framework (DS2OS) dataset. The Modbus dataset, popular for its highlights, examined associations in a Supervisory Control and Information Securing (SCADA) framework, in which the climate dataset given a expansive sum od information. Both datasets have typical and atypical information such as cyber-attacks, making them perfect for cybersecurity applications. Five expansion plans are investigated, counting arbitrary oversampling, stratified oversampling, Destroyed, ADASYN, and Generative Antagonistic Systems (GANs). The DS2OS dataset get arrange activity and include noxious exercises such as surveillance and refusal of benefit (DoS) assaults. To address the lopsidedness, they tried with distinctive models, comparing the comes about between centralized and federated settings. Irregular inspecting and generative strategies (e.g., Destroyed, ADASYN, and GANs) strategies are utilized to extend information, center to rebalance course division and increment location exactness. Particularly, stratified and uniform irregular inspecting appear the foremost idealistic comes about with less mechanization overhead, though GAN-based increment, whereas successful, requires more computerization assets. This investigate appear the significance of indicating lesson awkwardness and gadget heterogeneity in FL based inconsistency discovery errands for IoT applications.

In [10] the creator proposed a strategy to construct a lightweight, semi-supervised interruption discovery framework (IDS) for IoT gadgets employing a adjusted K-means clustering calculation. The creator combined inspecting and interruption discovery around diverse layers of the IoT structure. The show applying two strategies: one for pattern information and one for peculiarities. The most center of the investigate is based on K-means calculation, a semi-supervised oddity discovery method. It prepared demonstrate on little set of labeled information. This FL strategy consent for real-time interruption discovery along disseminated IoT gadgets, minimizing vitality fatigue by localizing interruption location. This distance-based strategy consents the framework to adjust to distinctive agreement of ordinary and irregular information, making it successful in characteristic exceptions. The creator connected FL calculation where IoT gadgets locally prepare information and share combined insights with a worldwide server. The strategy is try utilizing the NSL-KDD dataset, a well setup of the KDD Container 1999 dataset, which is for the most part utilized for assess interruption location frameworks. Besides, they consider pointed the significance of collaborative learning between IoT hubs and the central combination in expanding

discovery precision without yielding information protection. The result appeared in inquire about that lightweight IDS can effectively distinguish interruptions in IoT situations.

In [11], the creators show a story approach for identifying cyberattacks in Mechanical Control Frameworks (ICS) misusing irregularity location handle, combined inside a (FL) structure. They expound an design that impact edge computing to carry peculiarity location locally at each fabricating location, on the other hand than conviction just on centralized cloud servers. This disseminated approach engage the preparing of time-series information more profitably, minimizing the suspension and transfer speed depletion regularly related with cloud-based arrangements. The creators apply a half breed show combining Variational Autoencoder (VAE) and (LSTM) systems to make strides the detection accuracy of irregularities within the time-series information. This show capture both short-term designs and long-term reciprocities, permitting it to find novel peculiarities indeed in energetic situations. Besides, they advance the discovery edge utilizing the Part Quantile Estimator (KQE) to refine execution, making the framework strong and flexible to changes in ordinary operational actions.

In [12], the creators display a strategy called "Peddle," a disseminated irregularity location framework arranged to recognize compromised gadgets in LoRa-enabled (IIoT) systems. Peddle works by look at the Carrier Recurrence Counterbalanced (CFO) of each gadget, utilizing this physical layer highlight as a interesting recognizable proof to identify inconsistencies meaning of cyberattacks. The framework applies (FL) to prepare an inconsistency discovery demonstrate in a privacy-preserving way, in which nearby security administrations prepare device-specific models that are at that point combined into a worldwide demonstrate by a removed security benefit. This approach solidifies the system's capacity to distinguish unused and obscure assaults whereas minimizing capacity overhead and protecting strength against cyber dangers. The technique of Peddle applies a few key procedures. At first, the framework accumulate information from IIoT gadgets, concentrating on their CFO activities. The neighborhood security benefit to begin with trains a GRU (Gated Repetitive Unit) demonstrate on this information to construct an most punctual inconsistency location profile. These nearby models are at that point transmitted to a inaccessible security benefit, where they are combined into a worldwide show utilizing FL. This worldwide demonstrate is ceaselessly upgraded and part to nearby administrations to refine location precision over time. show preparing is nonstop, permitting it to alter to unused information and refine its precision persistently. The GRU demonstrate is chosen for its capability in oversight

time-series information like organize activity and its roughly moo computational complexity, making it appropriate for real-time inconsistency location in resource-constrained IIoT environments.

In [13], the creators show a crossover peculiarity location demonstrate named ATRAF, concretely planned for Mechanical Control Frameworks (ICS) working inside the conditions of the (IIoT). The ATRAF demonstrate assembles Autoencoder, Transformer, and Fourier change procedures to effectively identify inconsistencies in time-series information whereas being lightweight and appropriate for utilization on resource-constrained edge gadgets. This model consolidates detection execution by utilizing the Autoencoder to play down information dimensionality and get transient steadiness, whereas the Transformer-Fourier piece methods groupings in parallel, refining both preparing speed and memory productiveness. The ATRAF show is combined into a FL system, guarantee that the framework remains flexible to explaining information designs where as lessening communication costs and computational resource exercise.

In [14], the creators show a (FL)-based approach to revise interruption discovery in (IIoT) systems. The paper pinpoint the confinements of centralized machine learning (ML) frameworks, which needs open information combination at a worldwide server and can arrangement with information protection. The displayed FL strategy permits each IIoT gadget to locally prepare a demonstrate utilizing its possess information, securing information security. Each gadget at that point exchange as it were demonstrate overhauls, instead of crude information, to a worldwide server. The server combine these overhauls to build a worldwide demonstrate, which is after shared back with the gadgets for encourage nearby preparing. The creators apply the FedAvg calculation for demonstrate gathering, which combines show parameters based on the measure of each client's dataset. This prepare rehash development to upgrade the model's execution. They assess their approach utilizing the Edge-IIoTset dataset and discover that it pick up an precision of 92.49%, near to the 93.92% precision of customary centralized ML models. The FL inquire about moreover overcomes challenges particular to IIoT situations, such as constrained information per gadget and the require for a incredible demonstrate in spite of information shortage. The structure is isolated into three key parts: Local-End Learnings, Learnings Dissemination, and Collected Worldwide Learnings, guarantee that interruption location remains viable and productive whereas securing information security.

In [15], the creators show a novel approach to pinpoint the challenges of inconsistency location inside FL situations by combining blockchain innovation. They put this combined strategy to an interruption location cases, pointing to progress both the straightforwardness and responsibility of the machine learning models. The creators apply a assent blockchain framework that logs aggregate upgrades to inconsistency location models, hence giving an unchangeable review path of demonstrate changes. This blockchain-based FL approach ease the hazard of ill-disposed assaults that might harm nearby models and concession the keenness of the worldwide learning prepare. By utilizing autoencoders for peculiarity location and putting combined averaging procedures, the creators guarantee that show upgrades are combined safely whereas safeing security. Their tryouts demonstrate that this combining presents as it were a humble execution overhead (5-15%) compared to conventional FL frameworks, but important strengthens straightforwardness and security. The paper highlights the achievable of this approach against diverse neural organize structures and interruption discovery cases, displaying its potential for broader applications in cybersecurity. The gathering of FL and blockchain, as laid out, simply equalizations the require for strong inconsistency location with concentrated responsibility and auditability.

In [16], the creator presents a novel clustered (FL) structure planned to move forward organize peculiarity location in large-scale, heterogeneous IoT systems. This strategy pinpoints the one of a kind challenges postured by IoT situations, consolidating the differing equipment and computer program of gadgets, their tremendous scale, and their sending in uncontrolled settings. customary security strategies struggle with these challenges, particularly with the quick improvement of dangers and the impediments of cloud or edge computing. To require these issues, the proposed structure applies FL to contrive prepare machine learning models against numerous parts, minimizing information unique and arrange overhead. A key inventiveness in this strategy is the combination of an unsupervised gadget clustering calculation into the FL pipeline, which bunches gadgets based on their behavior to handle the heterogeneity of IoT situations more safely. The structure performance was back employing a testbed with 100 rehashed IoT gadgets and distinctive genuine assault cases, building up its capability to oversee diverse sorts of assaults, counting botnets and malware. The framework includes lightweight autoencoder neural systems for inconsistency location, which are particularly appropriate for the drive of IoT gadgets. These autoencoders are prepared to distinguish preoccupation from typical arrange activity, hence

deciding potential security dangers. By and large, this clustered FL structure appear a critical headway in securing IoT systems by helping the effectiveness and precision of peculiarity location against a huge run of gadgets and assault scenarios.

In [17], the creators, Tuo Zhang and colleagues from the College of Southern California, present a structure called FedIoT for FL in IoT situations. This structure include the FedDetect calculation, which utilize progressed procedures such as the Adam optimizer and a cross-round learning rate scheduler to progress peculiarity discovery in conveyed IoT gadgets. FedIoT works on a layered engineering acclimating of an application layer, calculation layer, and foundation layer. The application layer conveys a one-line API for propelling combined preparing withnon-IID datasets and a profound Autoencoder demonstrate, whereas the calculation layer makes a difference distinctive FL calculations, counting FedAvg and FedOPT, with a specialized FedDetect for inconsistency discovery. The foundation layer combines lightweight communication APIs like MQTT and a specialized PyTorch library for on-device show preparing. The system's capacity is gauge on Raspberry Pi gadgets, demonstrating its fitness to distinguish a wide extend of assault sorts with substantial preparing time and memory costs. FedDetect assimilate both worldwide and personalized limit calculations to alter to distinctive scenarios, in this way giving a immaculate arrangement for real-world IoT cybersecurity challenges.

In [18], the creators display utilizing (FL) and Blockchain innovations to move forward interruption discovery frameworks (IDS) in (IIoT) systems. The paper, wrote by Saqib Ali, Qianmu Li, Abdullah Yousafzai, and their individual teach, pinpoints on tending to the security and protection challenges local in IIoT situations by combining these progressed strategies. FL apportion the preparing of machine learning models against different gadgets without solidify information, hence securing security whereas abusing decentralized information sources. Blockchain complements this by giving a secure, settled record that can confirm and review intercut and exchanges inside the arrange. The creators layout how FL can proficiently oversee disseminated information whereas sparing security, and how Blockchain can make strides the security of this handle. They inquire about the confinements of conventional centralized IDS strategies, which persevere from tall computational costs and security concerns, and highlight how the combination of these innovations can offer a more versatile and secure arrangement. The investigate too does diverse machine learning and profound learning strategies finally applied to

IDS, recognizing the require for solid strategies that absorb FL and Blockchain to point the particular challenges of IIoT networks.

In [19] "A FL Approach to Irregularity Location in Shrewd Buildings" by Raed Abdel Sater and A. Ben Hamza, the creators show a novel technique for finding peculiarities in IoT-enabled shrewd buildings utilizing FL. They utilize a multi-task learning worldview joined with a stacked (LSTM) show to strategy multivariate worldly information from numerous sensors whereas preserving information security. The proposed structure contain of nearby models prepared on soul information, and a worldwide show that combined these nearby models utilizing the FedAvg calculation. To progress protection, the framework utilizes secure combined methods through PySyft, guarantee that isolated upgrades stay scrambled. This combined method not as it were minimize preparing costs by avoid information centralization but too get speedier consolidating and different execution in both classification and relapse errands relate to centralized models. The creators build up the capacity of their demonstrate through tests on real-world datasets, highlighting imperative enhancements in inconsistency location and vitality combination expectation in savvy buildings. Their display incorporate the combination of FL with privacy-preserving components and the rise of a strong, adaptable peculiarity discovery framework custom-made for IoT situations.

In [20] "An Outfit Profound Federated Learning Cyber-Threat Chasing Show `IIoT` " by Amir Namavar Jahromi, Hadis Karimipour, and Ali Dehghantanha, the creators display a FL based show arranged to make strides cybersecurity in IIoT situations without yielding information protection. The demonstrate utilize an outfit strategy, where two parallel FL fixing assess organize data one centering on typical operation and the other on danger possibilities. These components are built utilizing Stacked Autoencoders (SAEs) and prepared locally on client gadgets, giving as it were the encoder parameters with a worldwide server to maintain information protection and avoid antagonistic assaults. The worldwide models created from these nearby components are at that point abuse to prepare one-class classifiers (OCSVM and Confinement Timberland) on each client, which are afterward combined into a classifier holder for collaborative danger discovery against the arrange. The creators build up that their show beats existing strategies in f1-score, keeps up steadiness over shifting client numbers, and minimize preparing time compared to worldwide models. The key show incorporate the combination of FL for privacy-preserving danger discovery, the innovative utilize of segregated ordinary and danger information models to handle imbalance

information issues, and the execution of a classifier band for strong cyber-threat chasing in IIoT systems.

In [21] "Unified Profound Learning for Peculiarity Discovery within the IoT," Wang et al. (2023) show a novel strategy for identifying anomalies in IoT systems employing a mix of Profound Neural Systems (DNN) and (FL). The key help is the improvement of a decentralized inconsistency discovery framework that ensures protection by preparing models locally on IoT gadgets and giving only the overhauled weights with a worldwide server, instead of crude information. The creators utilize Common Information (MI) for highlight determination, making strides the model's precision by centering on the foremost related highlights from the IoT-BoTNet2020 dataset. The strategy incorporates normalizing the information, selecting ideal highlights utilizing MI, and preparing the DNN show with these highlights. The FL structure combine models from numerous IoT gadgets, building a worldwide show that's apportioning to the gadgets for assist advancements. The proposed strategy refine exactness and minimize wrong alert rates allude to conventional strategies. The consider too survey diverse FL combination methods to make strides demonstrate security and execution, setting up the proficiency of FL in tending to the challenges of suspension, security, and transfer speed in centralized IoT inconsistency discovery systems.

In [22], the creators Bahar Farahani and Amin Karimi Monsefi display a novel approach for making strides keen and collaborative (IIoT) frameworks by combining (FL) and a combined information space structure, which they pronounce can overcome the challenges of demolished and siloed information against diverse mechanical divisions. The proposed structure impact privacy-preserving machine learning (PPML) strategies, edge-fog-cloud computing, and a decentralized structure to encourage secure cross-company collaboration, in this manner indicating key challenges in information sharing and protection. Their strategy is grounded in a five-layer pyramid show that measures from edge gadgets to cloud computing, each layer performing particular errands such as information administration, analytics, and communication. Byjoining these advances, the creators point to form a adaptable and proficient IIoT living space that makes a difference prescient upkeep, condition checking, and other AI-driven applications. Through a case consider on agreeable prescient diagnostics, they substantiate the potential of this structure to refine real-time decision-making and data-driven perceptivity whereas validate information sway and compliance with Reasonable (Findable, Open, Interoperable, and Reusable) standards. The

structure, as nitty gritty, highlights the collaboration among edge and cloud computing to handle latency-sensitive errands locally whereas applying cloud assets for complex analytics and long-term information capacity, in this way forming a robust structure for end of the of Industry 4.0.

In [23], the creators display a novel decentralized and differentially private FL based interruption location framework (2DF-IDS) particularly construct for mechanical IoT situations, joining a few progressed procedures to make strides cybersecurity. The framework connect a decentralized FL strategy to reduce the dangers united with a single point of failure, normal in ordinary FL frameworks, by requesting demonstrate preparing against different hubs without a worldwide server. To guarantee information security, the framework utilizes a differentially private slope trade component, which includes controlled commotion to the show overhauls to preclude the spillage of delicate data. Also, the 2DF-IDS retain a secure key trade convention to securing communications between nodes, exploiting post-quantum cryptographic procedures like the Ring-Learning With Mistakes (Ring-LWE) issue to secure against quantum computing-based assaults. The creators, counting Othmane Friha and Mohamed Amine Ferrag, substantiate the productivity of 2DF-IDS through broad tests utilizing real-world mechanical IoT datasets, appearing that their strategy achieves high exactness in identifying diverse cyber dangers whereas considerably revising security and security in comparability to existing solutions.

In [24], the authors show a novel personalized FL structure for organize activity peculiarity location, utilizing a joining of strategies such as information combination with protection assurance and demonstrate fine-tuning to point the challenges of moo precision and tall untrue alert rates in routine strategies. The structure combines an LSTM-autoencoder demonstrate for identifying inconsistencies in organize activity, which forms multi-dimensional highlights induced from bundle and session stream levels, and employments discrete wavelet change (DWT) for refining include representation. The LSTM-autoencoder is prepared on normalized datasets, letting the location of unusual activity by reviewing reproduction blunders against a set limit. Besides, the proposed FL structure, named FedPAD, help designated demonstrate preparing against educate without yielding information protection, utilizing homomorphic encryption and the FedAvg calculation for show combination. The structure too assimilates private learning by fine-tuning models to account for neighborhood information dissemination contrasts, in this manner revising the generally discovery precision and vigor of the irregularity location framework.

In [25], the creators display the FL Empowered Profound Interruption Location (FLDID) structure, pointing to approach cybersecurity challenges in keen fabricating businesses. This structure utilize a half breed profound learning demonstrate, combination Convolutional Neural Systems (CNN), (LSTM) systems, and Multi-Layer Perceptrons (MLP) to identify cyber dangers. The approach acclimatize FL to empower numerous businesses to concert prepare a strong demonstrate whereas indicating the issue of restricted assault information in person divisions. To secure communications between edge gadgets and the central server, the FLDID structure utilizes Paillier-based encryption, guaranteeing the security of demonstrate angles. The structure technique incorporates initializing show parameters, scrambling and combining demonstrate slopes, and performing decoding for nearby overhauls. Exploratory comes about legitimize that this half breed show surpass existing procedures in recognizing cyber dangers, building up the viability of combining FL with progressed profound learning structure in a secure manner.

In [26], the creator presents broad examination of (FL) and its headways, with an center on its application in Industry 4.0 and edge computing. Methods and strategies secured incorporate Combined Averaging (FedAvg), which combines neighborhood show upgrades from clients to make a worldwide show, indicating difficulties related to non-independent and indistinguishably conveyed (Non-IID) information and tall communication costs. The paper appears the advancement of FL from conventional centralized machine learning to decentralized strategies, such as (HFL), Vertical (VFL), and (FTL). It subtle elements protection conservation strategies, including secure multiparty computation and differential protection, to guarantee information security. The creator too focuses show optimization procedures to refine FL execution, such as centroid distance-based FedAvg and nonconcurrent overhauls. Also, the paper appear appearance ways for utilizing models to distinctive client needs and inspiration components to persuade interest. The affect of FL on financial variables and the advancement of stages and instruments like Destiny and TensorFlow Combined are also reviewed, provide an including see of FL's conceivable to convert `IIoT` applications.

In [27], the creators display a novel strategy for moving forward peculiarity discovery in FL situations by combining blockchain innovation. The strategies they utilize incorporate a authorization blockchain-based FL demonstrate where dynamic overhauls to an peculiarity discovery machine learning demonstrate are report on a designated record. This strategy, created by Davy Preuveneers and colleagues from imec-DistriNet-KU Leuven and MTA SZTAKI,

includes utilizing an autoencoder for peculiarity location and focuses the challenge of antagonistic assaults on FL frameworks by guarantee obliged and translucence within the demonstrate preparing prepare. The creators illustrate that whereas encapsulating blockchain includes complexity, it as it were marginally impacts execution (between 5 and 15%) whereas giving vigorous reviewing office. Their strategy grants for FL without concentrate preparing information, making it significant to diverse neural organize structure and utilize cases, as illustrate by their comes about with the CICIDS2017 interruption discovery dataset. This creative joining of FL and blockchain gives a down to earth arrangement to refiner the discovery and mindful of pernicious exercises in a disseminated machine learning framework.

In [28], the creators Enrique MÃ¡rmol Camposet al. show an approach to move forward interruption location frameworks (IDS) in (IoT) situations by misusing (FL). They point the challenge of conventional centralized ML-based IDS frameworks that require information sharing, hence expanding protection instability. To soothe this, they apply a FL enabled IDS that employments multiclass classification methods, particularly multinomial calculated relapse, to identify distinctive assaults. Their investigate evaluate the effectiveness of this strategy through a few scenarios based on the ToN_IoT dataset, which they sectioned by IP addresses to expect diverse information disseminations. They see into the affect of combining capacities like FedAvg and Bolstered+ on execution, commenting that Bolstered+ offers renewal over FedAvg by indicating issues related to non-iid and skewed information disseminations. This work distinguishes the require for specialized datasets and fine-tuned combination strategies in Federated settings to progress IDS execution and security in IoT applications.

In [29], the creators display utilizing (FL) procedures for making strides interruption discovery frameworks (IDS) whereas indicating protection and productivity challenges. Shaashwat Agrawal and colleagues think about diverse FL procedures such as (DRL) and Consideration Gated Repetitive Units (FedAGRU) to refine peculiarity discovery productivity. The creators contend how FL indicating protection concerns by preparing models locally on edge gadgets instead of pass on crude information to worldwide servers, in this manner mollification dangers of information breaches and security infringement. They see into strategies like scrambled show parameters and secure communication conventions to forestall information spillage and demonstrate turn around engineering. The audit moreover valuation diverse IDS sending structure, counting centralized, dispersed, and unified setups, highlighting predominance in versatility and

diminish server bottlenecks. The paper recognizes challenges such as communication overhead and inactivity, and deliver future inquire about bearings for optimizing FL in IDS, including headways in secure information administration and altering demonstrate vigor against attacks.
In [30], the creators show the FL base Cyber Risk Insights System (FL-CTIF) for making strides security in (IIoT) situations through a joining of (FL) and Data Combination (In the event that) methods. This structure points to point the impediments of conventional Interruption Location Frameworks (IDS) that depend on out of date assault designs by assimilate upgraded and broad cyber danger insights. The FL-CTIF structure includes planning a FL based Manufactured Neural Arrange (ANN) show that fortifies precision and minimize wrong positive rates through a common dataset consolidating strategy. Particularly, the creators make broad cyberattack dataset by combine highlights from the CIC-DDoS2019 and ToN_IoT datasets, overhauling the detection fitness for distinctive assault vectors like ARP harming, SSL-based assaults, and DNS surges. The FL component allow for concert preparing of nearby models against diverse IIoT sub-departments, with a worldwide security officers combining and maximizing the show based on execution measurements such as accuracy and computational effectiveness. The method contain a few steps: collecting and consolidating assault datasets utilizing social polynomial math, preparing nearby models with overhauled datasets, and utilizing a satisfaction-based scoring framework to advance preparing rounds and minimize CPU absorption.

In [31], the authors present a Privacy Preserving and Traceable Federated Learning (PPTFL) structure to pinpoint privacy and traceability issues in industrial IoT (IIoT) applications. They present Hierarchical Aggregation Federated Learning (HAFL) as a technique to denigrate privacy breaches and computational overhead by employing AES-EAX encryption for secure data propagation. HAFL incorporates numerous layers where nearby structures are not progressively scrambled, conveyed, and interconnected. This approach guarantees that indeed in the event that information collectors collect information, no client profile can be learned due to extra clamor and encryption. Moreover, the creators coordinated the blockchain with the InterPlanetary Record Framework (IPFS) to make strides security and execution. Whereas the blockchain stores unchanging information from the preparing prepare, IPFS oversees the capacity of benchmarks to guarantee information keenness and avoid altering. This combination decreases computational and communication costs compared to conventional strategies, guaranteeing that FL is precise and

effective. All comes about illustrate the predominance of PPTFL over existing arrangements, illustrating its preferences in terms of precision and computational productivity.

In [32], the authors proposed the concept of Propagation-Proof Data Aggregation Federated Learning (PPDAFL) to explicitly address privacy issues in IIoT. The paper by Hongbin Fan and Zhi Zhou proposes a way to fend shared and federated data without compromising sensitive information. They use (FL) to train models by merging local training models instead of sharing the original data. To improve security and avoid reverse analysis attacks, the Practical Byzantine Fault Tolerance (PBFT) algorithm is applicative, where a selected IIoT device in each combination area launching data accumulation. Additionally, the authors absorb the Paillier cryptosystem and secret sharing methods to further improve data privacy and resilience. Shamir's secret sharing scheme, based on Lagrange interpolation, is used to securely allocate data among multiple partakers, attesting that a slightest number of secret holders is necessary to rehabilitate the secret. The security analysis substantiates through the way efficiently minimize computation and communication overhead while securing data factuality and integrity in a decentralized IIoT environment. The study sharpen on solving the issue of "data islands," where industrial data cannot be freely shared due to privacy uncertainty. Through this method, the PPDAFL scheme provides a robust structure for secure data combination in IIoT applications, allowing for the effectuation of intelligent constructing.

In [33], the authors present an new approach for asynchronous federated learning-based threat detection using a method called Delay Compensated Adam (DC-Adam). This technique pinpoints the critical challenge of gradient delays in non-IID (non-Independent and Identically Distributed) data environments, typical in IoT and Cyber-Physical Systems (CPS). To alleviate gradient incongruous arising from asynchronous communications against distributed nodes, the authors introduce a Taylor Expansion-based scheme to redress for overdue gradients. Furthermore, they design a pre-shared data training policy for non-IID data to assure model confluence. The training process assimilate three key steps: warm-up for weight parameter launch, model training with delayed gradient satisfaction, and anomaly detection execution. The proposed method shows state-of-the-art methods, improving accuracy, precision, recall, and F1 score. Additionally, the authors validate their system through both theoretical convergence analysis and practical results, evidencing its capability in distributed threat detection, individually in resource-constrained IoT devices. By joining adaptive learning rates from the Adam upgrading algorithm with delay

satisfaction, the DC-Adam approach proves highly productive for real-time threat detection in complex, distributed computing environments.

In [34], the authors present a new structure absorb (FL) and blockchain technology to pinpoint security, privacy, and efficiency challenges in the (IIoT). The research accent the limitations of traditional Domain Name Systems (DNS) for IIoT recognition, citing concerns over time delay, security, and stability. To address these, they employ blockchain's decentralized and secure data storage and FL's privacy-preserving mutual learning methods. Specifically, they apply cryptographic techniques like asymmetric encryption, digital signatures, and public key infrastructure (PKI) to assure system security, while present a key and authentication mechanism for supervise access rights against different user types. The blockchain's attributability feature helps securely record equipment status against the supply chain, and FL helps refine machine learning on distributed IIoT devices without centralizing sensitive data. Furthermore, the authors present a communication-efficient top-k algorithm to minimize overhead from iterative model training and introduce using Gaussian noise for differential privacy to protect against data inference attacks. Finally, they analyze their structure through a Convolutional Neural Network (CNN) model on a dataset and report that their method get high classification accuracy, establishing the structure possible for secure, scalable IIoT applications.

In [35], the authors proposed a new model called FL-IIDS (Federated Learning Based Incremental Intrusion Detection System) to detect malicious behaviors in FL-based intrusion detection systems (IDS). Their approach explicitly addresses the problem that subsist IDSs often process static data and therefore forget old categories when learning new tasks. FL-IIDS introduces a novel workflow that combines gradient-balanced classes and a sophisticated model to balance the learning between new and old classes. They also use a relay-user fusion model to account for global disremember while preserving private information. The authors found that their system can effectively support past memories without interfering with the discovery of new groups. The model is based on the FedAvg algorithm and uses technologies such as model memory, category gradient measurement, and information extraction. Evaluate of data such as UNSW-NB15 and CICIDS2018 has confirmed the effectiveness of the model in reducing memory loss while maintaining the accuracy of research results.

In [36], the authors present a new approach using different ML techniques for improving intrusion detection systems (IDS). They research techniques like adaptive resonance theory, genetic algorithms, clustering, fuzzy logic, convolutional neural networks (CNN), recurrent neural networks (RNN), and deep auto-encoders to refine anomaly detection capacity. These methods, especially AI-based techniques, help pinpoint challenges posed by zero-day attacks, which traditional signature-based systems may miss. The authors also examine with distributed and hierarchical structure for IDS, emphasizing how decentralized models better habits environments like cloud systems and IoT, with specific focus on smart home setups.

In [37], the creators, a define structure for making strides interruption location in Mechanical IoT utilizing FL and profound generative procedures, particularly Conditional Generative Antagonistic Systems (c GANs). The structure comprises of three center models: a combined generative demonstrate for finishing different manufactured information to vanquish imbalanced datasets, a Faultfinder demonstrate for characteristic genuine from produced information, and a Classifier for deciding cyber dangers. Fed Gen ID coordinated a interesting approach by allowing clients to locally prepare the c GAN's Faultfinder and Discriminator, refining versatility against ill-disposed assaults and improving security. The Wasserstein misfortune with Angle Punishment is utilized to preserve preparing and guarantee practical information era. Moreover, Fed Gen IDs FL pattern combines demonstrate overhauls against dispersed clients, overhauling both discovery precision and conception in IIoT situations, particularly for zero-day assaults. The creators conception the model's adequacy employing a modern mechanical cybersecurity dataset, appearing predominant execution over customary approaches by 10% in danger discovery beneath tall protection rule.

In [38], the creators propose FL-MGVN, a novel demonstrate for peculiarity location by join FL and a blended Gaussian variational self-encoding arrange (MGVN). The MGVN component employments a blended Gaussian earlier to collect a dubious self-encoder, which citations information highlights for truncate into a negligible hypersphere through a profound bolster vector arrange (SVDD). This hypersphere parts typical information from atypical focuses by calculating their Euclidean separate to the center. The FL way of FL-MGVN empowers collective preparing of a worldwide demonstrate among different members without sharing private information. This guarantees security and calm the need of labeled information common in irregularity location assignments. The method show an evaluation on datasets like NSL-KDD, MNIST, and Fashion-MNIST, evidencing predominant execution and classification exactness. The normal zone beneath

the bend (AUC) come to 0.954 and 0.937 on MNIST and Fashion-MNIST, exclusively, suggesting tall peculiarity location capabilities. The union of FL with the MGVN show pinpoints both the security concerns and exactness impediments of current peculiarity location technologies.

In [39], the creators display Block chained-Federated Learning-based cloud interruption discovery conspire (BFL-CIDS) for apportioned noxious assault location in IoT gadgets. The strategy impact FL to combine nearby preparing information from edge gadgets into a worldwide anticipating demonstrate whereas moving forward security and protection utilizing blockchain innovation. The structure contains four key layers: the Application Layer, Federated-Learning Layer, Chaincode Layer, and Blockchain Layer. The arrangement presents methods just like the Fed Avg algorithm for demonstrate combination and a modern caution channel recognizable proof module (AFI) to play down wrong cautions, which enhances the precision of the FL demonstrate. The blockchain guarantees information attributability and astuteness by putting away preparing parameters and models, avoid fiddling amid transmission. Key components of the plot includes Learning-disabled Hubs (LN), Territorial Benefit Parties (RSP), and a Worldwide Preparing Party (GTP), which relate distinguish and classify arrange inconsistencies. The paper too gives the Apriori calculation and semi-supervised learning for visit points of interest mining and untrue caution sifting, giving to more viable and solid IoT security.

In [40], The paper presents Edge-IIoTset, a comprehensive cybersecurity dataset tailored for IoT and Industrial IoT (IIoT) applications, supporting both centralized and federated learning. Created from a seven-layer testbed combining advanced technologies such as ThingsBoard, Hyperledger Sawtooth, and ONOS SDN, the dataset features traffic from over 10 types of IoT devices and simulates 14 cyberattacks grouped into five threat categories, including DoS, man-in-the-middle, and malware. Key contributions include the realistic testbed system, diversity in IoT protocols (e.g., MQTT, Modbus), and a enhanced feature set of 61 high-correlation attributes out of 1176 extracted using Zeek and TShark. The dataset enables evaluation of ML/DL models in both centralized and privacy-preserving federated settings, with reported accuracies of up to 99.99% (binary classification) and 94.67% (15-class) in centralized learning, and up to 100% (IID) and 93.37% (Non-IID) in federated learning. While its realism and protocol coverage offer strong advantages, limitations include the resource-intensive testbed and a fixed attack scope, positioning Edge-IIoTset as a valuable but expandable benchmark for intrusion detection in IoT/IIoT cybersecurity.

In [41], authors Z Cao, B liu, D Cao, D Zhou, X Han and J Cao write a research paper titled as "A Dynamic Spationtemporal Deep Learning solution for Cloud-Edge collaboration Industrial control System Distributed Denial of Services Attack Detection" in 2025. Research focus on DDOS attack detection in Cloud-Edge Industrial Internet of Things (IIOT). In the research work authors used two datasets named as CIC DDOS2019 and Edge-IIOTset for model training. The CIC DDOS2019 dataset has 13 different attack types such as HTIP floods, UDP floods and Edge-IIotset has 14 different types of attacks types such as HTTP floods and TCP SYN floods. In data preprocessing data is converted into packet array structure. These packets are combined according to time-based. Missing data is replaced by zero and each data is presented in normal and attack traffic. For model training 20 top network traffic features are selected. The dataset is split in 80% training , 10% validation and 10% for testing. From both datasets 5% of data is saved for global model performance. The research work introduce the FedDynST model that use federated learning structure for DDOS attack detection using DDOS detection modules. The APPNP graph convolutional network GCN build a static and dynamic structure to capture Short-Term and Long-Term parameters in data features. 1D-CNN model is used to get the parameters from the datasets. Adam optimizer is used with 0.005 learning rate to train the model. 5 local model rounds are used with 100 batch size. The dynamic weights of each client is calculated using divergence metrics and normalized training loss. Trained FedDynST model achieved 99.37% accuracy on CIC DDOS2019 dataset and 99.94% accuracy on Edge-IIotset dataset. The proposed research has many limitation like used GNN model introduce computational complexity on limited number of low resource devices. The research need to focus on real world structure with encryption and noise techniques and adversarial attacks structures to secure and private data with efficient performance. In [42], authors A A.Alashdadi, A Ali Almazori, N Ayub, M D.Lytras, E Alsomali, F S.Alsubaei and R Alharbey write a research paper titled as " Federated deep learning for Scalable and Privacy Preserving Distributed Denial of Services Attack detection in Internet of things Networks" in 13 Feb 2025. In this research framework authors used three datasets named as CIC DDOS 2019, UNSW-NB15 and IOT23. These datasets have normal and attack data networks traffic. In data preprocessing three different techniques are applied. First is Adaptive feature Normalization(AFN) that scale distributed features in distributed network traffics groups like normal and attack groups. Second is Multi-scale Temporal Balancing (MTB) which is used to redistribute imbalanced classes samples into temporary groups. These groups show balanced structured of attacks types. Third is

Contextual Traffic Aggumentation (CTA) by using this method authors show the temporary parameters of contextual connections of surrounding samples weights. After this Dynamic Proportional Class Adjustment (DPCA) is used for more class balance of weight sampling. To adjust data features for reducing connections Dual Adaptive Selector (DAS) applied for conditional convariance matric. In the model design hybrid structure of RESVGG-SwinNet method is used for feature extraction. VGGNet is used to refine it and SwinNet Transformer is used for long parameters capturing. Model training is based on federated learning with 0.001 learning rate , dropout with 0.3 and batch size of 64. Each local model is iterate for 5 round and the local models updates are combined using federated averaging (FedAvg). To reduce the communication overhead model aggregation is done after 30 rounds. To reduce computational resources quantization and pruning method is used. These methods achieved 2.5ms of inference time. Proposed model FL-RESVGG-SwinNet achieved accuracy of 99.0% with Multi-label Sensitive Index (MSI) of 97.5% and False Alarm Rate (FAR) is 2.5%. The ROC results are .993%. Research has many limitations like more than 20 % packets are lost that reduce 60% of detection rate. Research has mostly focus on one attack type DDOS, may this model not properly work on zero attack type. This research needs to future work on applying neural networks and encryption to train the secure and private model on local and server side.

In [43], authors R H.Alamir, A Noor, H Almukhilfi, R Almukhilfi and T H.Noor proposed a research paper titled as " SecFedDNN: A Secure Federated Deep Learning Framework for Edge-Cloud Environments" in 12 Jun 2025. A hybrid method is used that integrate both deep learning and deep neural network for security and privacy in intrusion detection systems. In this research TON-IOT dataset is use which contain DDOS DOS and injunction attacks types. Dataset is divided in two parts for training and testing, 80% is used in training and 20% is used in testing. For centralized training three different deep learning models are applied. First is Simple neural network (SNN) second is Long Short-Term Memory (LSTM) and third is Deep neural network (DNN) SecFedDNN model is utilized on federated learning setup , within this structure four layers are applied. First is Device layer that train local models on local devices, second is Edge layer which is used for data preprocessing and intrusion detection, third is federated learning layer that secure and private data on local and server side also use federated averaging for model aggregation, and the last layer is cloud layer that enhance and apply global model on the system. The SecFedDnn model get accuracy of 84.6%, precision of .846%, recall of 0.834% and F1-score is 0.83% on the

local clients. Also the model gets average accuracy of 84% on all clients and the average response time is 25.5 to 30.1 second. The research has many limitations that cause data overloading on few numbers of local devices. Research focus on only three attack types that case low performance on other attack types. Research need future work on applying secure multi-part computation and fully homomorphic encryption that secure the process of global model aggregation.

In [44], authors H Peng, C Wv and Y Xiao write a research paper titled as "FD-IDS: Federated Learning with knowledge Distillation for Intrusion Detection in Non-IID Iot Environment" in 10 July 2025. In this research work authors used two dataset named as Edge-IIoTset and N-BaIot for model training and attack detection. In the preprocessing work first they remove all missings values than features are scaled using Z-Score normalization and apply one hot encoding on the target features. Top 25 features from Edge-IIoTset and top 71 features are selected for model training and reduce complexity. This method reduce 9.07% of running time from Edge-IIoTset and 6.34% running time from N-BaIot dataset. Researchers apply deep neural network for strong features extractions with the learning rate of 0.001. In the research nine local model and one server model is used for training. The global model is aggregated using Federated Prox algorithm that reduce drift from the global model. Knowledge Distillation method is used in federated learning iterations. The global model accuracy is 93.86% on Edge-IIoTset and 83.81% accuracy on N-BaIot dataset. By using knowledge distillation with non-IID it reduce the false negative rate (FNR) from 8.11% TO 6.14%. The proposed model FD:IDS on high Non-IID rate on Edge-IIoTset dataset perform the accuracy of 93.86% as compared to SIM-FED model whose accuracy is 91.21%. The research has limitations that case the low performance as compared to advanced neural networks. In data processing mostly data is removed which is value able, many important feature is missing. Need to focus on data preprocessing techniques and cryptographical techniques for better performances.

In [45], authors S Kumar GK, K Prakash K, B Muniyal and M Rajarain write a research paper titled as "Explainable Federated Framework for Enhanced Security and Privacy in Connected Vehicles Against Advanced Persistence Threats" in 04 June 2025. In this research federated learning is used for detection of anomalies in IOT- enabled Connected Vehicles. In methodology Horizontal federated learning is applied on local clients using differential privacy to secure updates. In this research three datasets are used named as UNSW-NB15, Edge-IIoTset and CSE-CIS-IDS2018. The main focus of this research is to detect and find Advance Persistent Threats

(APT) using deep convolutional learning neural networks. To identify the high values features Shapley Additive exPlaination (SHAP) method is applied. Each local model has fixed number of iterations using DL-CNN model with applied noise. Proposed method PF-DAPTIV get the accuracy performance of 97.32% for UNSW-NB15, 96.81% for Edge-IIoTset and 98.06% for CSE-CIC-IDS2018. After applying noise on proposed method it reduce 2% to 3% of overall accuracy of trained model. The proposed research has limitations like it only focus on APT attack that may reduce performances of zero attack type. Limited number of local clients increase computational work. Research need to apply neural network technique that see data in different sequences.

2.4 Analysis of Existing Techniques

In this section, we handle a thorough investigation of the existing techniques inspect in the literature, focusing on how they point key challenges in federated learning, secure computing, and anomaly detection against different areas. The process is manage around the core methodologies and strategies engaged by researchers to undertake difficulties related to privacy, security, scalability, and efficiency in industrial systems.

2.4.1 Federated Secure Computing

The assessment starts with federated secure computing systems, where the main focus is on splitting industrial logic from cryptographic operations to guaranty data privacy. The existing techniques in this domain authority a client-server structure, which permit individual data owners to conserve control over their data by running their own servers. These techniques have valid effective in securing privacy by avoid sensitive data from being shared above the cryptographic layer. The adaptability and efficiency of these systems, concretely in handling different hardware form, make them proper for a broad range of applications, from IoT devices to larger network structures. However, while these systems are lightweight and open-source, they forehead challenges in terms of absorption with existing structures and assure unchanging performance against different environments.

2.4.2 Federated Learning for Predictive Maintenance and Anomaly Detection

Next, we explore federated learning techniques apply on predictive maintenance (PdM) and anomaly detection, especially in industrial settings. The usage of advanced deep learning models

like 1DCNN-BiLSTM within federated learning structure establishes important conceivable in protecting data privacy while letting efficient training on distributed datasets. These techniques allow local models to be trained on separate devices, with updates combined at a global server, thus improving the reliability and accuracy of PdM systems. However, the challenge lies in expanding these models for changing data quality and accessibility against different devices, as well as attest timely model updates to detect anomalies in real-time.

2.4.3 Integration of Federated Learning with Edge Computing and Blockchain

The accumulation of FL with edge computing and blockchain technology describe a important advancement in securing distributed machine learning environments. Techniques in this area focus on exploiting the computational power of edge servers for local model training, while blockchain technology is used to handle and secure model updates. This brief address important issues of security, confidentiality, and compliance by ensuring the integrity of instruction programs developed with sensitive information and out-of-control management in the region. However, these methods are often difficult to implement and require a high level of creativity and careful coordination of various partners.

2.4.4 Federated Learning for Anomaly Detection in Smart Buildings

In the context of smart buildings, FL vulnerability detection techniques are being examined for their ability to protect the large amounts of data generated by IoT sensors while preserving privacy. The use of LSTM models in authority allows for unobtrusive monitoring and anomaly discovery without the need for data collection, enabling secure and operational solutions for smart home operation. This technology should reduce the threat of data breaches and lead to a better understanding of structure management. However, there is still a gap in ensuring interoperability between various IoT devices and conserve accurate fault detection for various sensor types and data streams.

2.4.5 Privacy-Preserving Federated Learning Models

Privacy-preserving FL models, such as the FREDY model, are being tested for their effectiveness in protecting sensitive data during learning. This model uses different privacy techniques to add noise to the data structure to prevent attackers from predicting the occurrence of certain details. The evaluation highlights the trade-offs of these processes against privacy and helps validate

training standards. Although these models provide strong protection against privacy attacks, they suffer from the lack of accurate models and the computational burden required to implement them in the privacy management process.

2.4.6 Anomaly Detection and Behavioral Fingerprints in IoT Networks

The development of global behavioral fingerprinting for intrusion detection in the Internet of Things is a challenging area of research. Discover how FL, when combined with homomorphic encryption and blockchain, has the potential to improve the security and scalability of IoT systems. This technology is designed to cover against various types of attacks, such as Denial of Service (DoS) and Sleep Deprivation Attacks (SDA), by rapidly detecting and mitigating malicious behavior. However, the intricacy and revealing financial investment imperative to achieve this process may hinder its widespread adoption.

2.4.7 Intrusion Detection Systems Using Federated Learning

The assessment also includes FL intrusion detection systems (IDS) that aim to manage private data while enrich the accuracy of threat detection. Both horizontal and vertical learning form were interrogate demonstrating their ability to train global models without providing original data. These technologies are particularly important in environments where particular information is important, such as financial institutions and healthcare association

2.4.8 Lightweight and Semi-Supervised Intrusion Detection for IoT

Finally, this section evaluates a lightweight, semi-supervised access detection approach for IoT devices. These systems use a modified K-means algorithm in a joint learning architecture to identify access points in real time while minimizing power consumption. Tests show that these systems are well suited for low-budget regulator and are suitable for IoT applications where battery life and performance are important. However, the need for uninterrupted adjustment to changing data patterns and the potential trade-offs between detection accuracy and energy efficiency are ongoing challenges in this environment.

2.5 Literature Review Summary

This well-organized summary table help in drive the large literature in our field. It improves a structured review of the different techniques and perspective embraced by researchers by grouping studies into important categories.

Table 1: Literature Review

Year & Authors	Title	Contribution	Advantages	Limitations
2021 H. Ballhausen and L. C. Hinske	Federated Secure Computing	Middleware bridges client logic and cryptographic backend. Supports diverse client-server topology configurations. Simplifies secure computing via microservices and APIs. Enables data privacy with modular architecture. Integrates cryptographic protocols seamlessly into applications.	Separation of concerns simplifies development. Flexible for various client-side languages. Lightweight clients work on limited resources. Scalable microservices enhance adaptability. Maintains strict privacy and data segregation.	- Complex server-side cryptographic setup. Thin clients restrict advanced client-side tasks. Central nodes risk latency bottlenecks. Protocol compatibility limits some integrations. Requires rigorous security measures for production.
2023 J. Ahn, Y. Lee, N. Kim, C. Park, and J. Jeong	Federated Learning for Predictive Maintenance and Anomaly Detection Using Time Series Data Distribution Shifts in Manufacturing Processes	Introduces 1DCNN-BiLSTM for predictive maintenance. Adapts federated learning to handle data shifts. Uses cold start and EDC for improved performance. Enhances anomaly detection in manufacturing environments	Maintains client data privacy using federated learning. Flexible grouping handles dynamic data distributions. Efficient anomaly detection in time-series data. Supports real-time communication in IoT settings.	Requires complex setup for federated learning. May face scalability issues with large clients. Performance relies on accurate clustering methods. Sensitive to initial data distribution variations.
2022 A. Alghamdi, J. Zhu, G. Yin, M. Shorfuzzaman, S.	Blockchain Empowered Federated Learning Ecosystem for	Introduces a federated learning (FL) network for	Ensures data privacy using federated learning and blockchain.	High complexity in managing decentralized edge servers.

Year & Authors	Title	Contribution	Advantages	Limitations
Alyami, S. Biswas, and N. Alsufyani	Securing Consumer IoT Features Analysis	secure, decentralized learning. Integrates blockchain for secure access and model storage. Utilizes certificate authority (CA) for authentication. Enhances privacy via local training without data sharing.	Scalable and decentralized, facilitating secure model updates. Offloads computation to edge servers for efficiency. Real-time model updates through blockchain-based consensus.	Resource-intensive for large-scale deployments. Sensitive to offloading decisions and computational resources. Blockchain's data storage could be inefficient for large models.
2021 R. Abdelsater and A. Benhamza	A Federated Learning Approach to Anomaly Detection in Smart Buildings	Introduces a novel privacy-by-design federated LSTM model. Enhances anomaly detection in smart buildings using IoT data. Combines multi-task learning for better sensor performance. Protects data privacy by not sharing sensor data.	Improved anomaly detection with federated learning. Preserves sensor data privacy through secure aggregation. Reduces central server computation load. Mitigates noisy or incomplete data issues.	Requires reliable network communication for federated learning. Local models may not capture all global trends. May face challenges in real-time processing for large-scale IoT systems. Sensor data quality directly impacts model performance
2023 Z. Anastasakis et al	FREDY: Federated Resilience Enhanced with Differential Privacy	Introduces FREDY, a federated learning framework. Uses teacher-student model training for knowledge transfer. Ensures privacy-preserving model	Privacy-preserving through differential privacy mechanisms. Protects sensitive data with federated learning setup.	Dependent on the quality of teacher models. Requires significant computational resources for training.

Year & Authors	Title	Contribution	Advantages	Limitations
		development for real-world tasks. Aggregates teacher model predictions using noise for privacy.	Efficient knowledge transfer using teacher-student model. Scalable for real-world applications with public data use.	Privacy guarantees rely on noisy aggregation, reducing accuracy. Public data may not always be sufficient for training.
2023 M. Arazzi, S. Nicolazzo, and A. Nocera	Fully Privacy-Preserving Solution for Anomaly Detection in IoT using Federated Learning and Homomorphic Encryption	Developed a privacy-preserving strategy for federated learning (FL). Utilized Secure Multi-party Computation (SMC) for privacy. Enabled privacy while identifying target nodes and aggregators. Ensured no attacks during the FL task setup phase.	Ensures privacy of identities in FL tasks. Efficient group formation for model training. Reduces risk of unauthorized access and attacks. Supports decentralized, collaborative learning without data sharing.	Computational complexity increases with more aggregators. Requires additional resources for secure delegation. Might have scalability issues with a large number of devices. Dependent on secure delegation for resource-constrained devices.
2023 A. Alazab , , A Khraisat, S Singh, and T Jan	Enhancing Privacy-Preserving Intrusion Detection through Federated Learning	Introduces horizontal and vertical federated learning. Enables collaborative model training with privacy protection. Helps build intrusion detection models without data sharing. Aggregates updates from local models to	Privacy preserved through local data model training. Scalable with multiple clients and data sources. Enhances intrusion detection across networks.	Requires significant computational resources for aggregation. Potential bias towards frequently updated clients. Slow convergence due to

Year & Authors	Title	Contribution	Advantages	Limitations
		create global models. Incorporates diverse data sources while preserving privacy.	Can be applied to various fields like healthcare and IoT. Protects sensitive data while sharing model updates	communication bottleneck. Complex setup for secure aggregation processes.
2024 A. Kaushik and H. Al-Raweshidy	A Novel Intrusion Detection System for Internet of Things Devices and Data	Introduces TLBO-IDS for intrusion detection. Combines TLBO algorithm with feature extraction. Uses the UNSW-NB15 dataset for training and testing. Reduces data duplication and overlap with data cleaning. Enhances intrusion detection accuracy with optimized features.	Efficient feature extraction speeds up training. Improves accuracy with RF classification model. Data cleaning prevents model performance issues. TLBO optimization ensures better feature selection. Scalable for large datasets like UNSW-NB15.	Computation-heavy due to feature optimization. Sensitive to data quality and consistency. Requires large dataset for optimal performance. May have slower convergence with large datasets. Performance could degrade with imbalanced data.
2022 B. Weinger, J Kim, A Sim, M Nakashima, N Moustafa, and K. John Wu	Enhancing IoT anomaly detection performance for federated learning	Used multiple IoT datasets (Modbus, Weather, DS2OS). Applied federated learning (FL) for anomaly detection (AD). Addressed class imbalance with various data augmentation techniques.	Provides a privacy-preserving model with FL. Enhanced anomaly detection using augmented data. Combats class imbalance effectively. Helps improve model performance in	Class imbalance remains a challenge in FL. FL increases the need for communication rounds. Large datasets can increase computational costs. Data augmentation

Year & Authors	Title	Contribution	Advantages	Limitations
		Tested FL in real-world IoT scenarios with multiple devices. Introduced GANs for data augmentation in FL.	distributed IoT networks. Can work with different types of IoT datasets.	might alter distributions. GANs introduce significant computational complexity.
2023 S. Hajj, J. Azar, J. Bou Abdo, A. Makhoul, J. Demerjian, and C. Guyeux	Cross-Layer Federated Learning for Lightweight IoT Intrusion Detection Systems	Applies K-means clustering for IoT intrusion detection. Integrates federated learning for data privacy. Introduces a cross-layer design for modular IoT IDS. Combines sampling and intrusion detection methods.	Lightweight and efficient for small IoT devices. Ensures privacy by avoiding data transmission. Reduces energy consumption through local anomaly detection. Scalable solution for IoT environments with limited resources.	Performance depends on data quality and distribution. May struggle with large or complex datasets. Limited by number of clusters and data points. Requires careful tuning of percentile for detection accuracy. Potential high false positives with low percentile settings.
2025, Zhigang Cao et al.	"A Dynamic Spatiotemporal Deep Learning Solution for Cloud–Edge Collaborative Industrial Control System Distributed Denial of Service Attack Detection"	- Proposed FedDynST, a DDoS detection model combining federated learning and deep learning. - Introduced static and dynamic adjacency matrices to capture long-term and short-term traffic patterns.	- Improved detection accuracy and convergence. Preserved data privacy through federated learning. - Validated on CICDDoS2019 and Edge-IIoTset datasets, showing superior performance.	- Limited to specific datasets (CICDDoS2019 and Edge-IIoTset). - Requires further validation in diverse industrial environments. - Dependency on labeled data for training.

Year & Authors	Title	Contribution	Advantages	Limitations
2025, Alshdadi et al.	"Federated Deep Learning for Scalable and Privacy-Preserving DDoS Attack Detection in IoT Networks"	- Proposed ResVGG-SwinNet, a hybrid model combining ResNet, VGGNet, and Swin Transformer for DDoS detection. - Introduced Dual Adaptive Selector (DAS) for feature optimization.	- Achieved 99.0% accuracy and 99.3% AUC on CIC-DDoS2019, UNSW-NB15, and IoT23 datasets. - Balanced computational efficiency (93.0% OES).	- Complex model may increase computational overhead. - Requires labeled data for training. - Limited to specific IoT scenarios (e.g., healthcare, smart cities).
2025, Alshdadi et al.	"Federated Deep Learning for Scalable and Privacy-Preserving DDoS Attack Detection in IoT Networks"	- Proposed ResVGG-SwinNet, a hybrid model combining ResNet, VGGNet, and Swin Transformer for DDoS detection. - Introduced Dual Adaptive Selector (DAS) for feature optimization.	- Achieved 99.0% accuracy and 99.3% AUC on CIC-DDoS2019, UNSW-NB15, and IoT23 datasets. - Balanced computational efficiency (93.0% OES).	- Complex model may increase computational overhead. - Requires labeled data for training. - Limited to specific IoT scenarios (e.g., healthcare, smart cities).
2025, Alamir et al.	"SecFedDNN: A Secure Federated Deep Learning Framework for Edge-Cloud Environments"	Proposed adaptive FL for DDoS detection in dynamic environments.	Client-driven training strategy for improved accuracy.	Limited to DDoS attacks, not other threats.
2025 (Kumar et al.)	Explainable Federated Framework for Enhanced Security and Privacy in Connected Vehicles Against Advanced Persistent Threats	PF-DAPTIV Framework: A privacy-preserving federated deep learning (FDNN) model for detecting APTs in IoT-enabled vehicles. Uses differential privacy (DP) and SHAP-based explainability.	- Privacy: DP ensures data confidentiality. - Accuracy: 95.63–98.06% detection rates.	- Trade-off: Privacy mechanisms slightly reduce accuracy. -Dataset Dependency: Relies on mapped features from non-APT datasets (UNSW-NB15, CICIDS2018).

2.6 Research Gap

- Existing research struggles to explore robust federated learning models in the Industrial Internet of Things (IIoT), where the impact of attacks can be more severe due to the system's sensitive nature.
- The research needs to be focus on enhancing communication and accumulation standards that can measure efficiency in large amount of IIoT deployments.
- The existing research struggle in extensive assessment of anomaly detection structure in IIoT network, and aptitude to detect and accommodate a west range of attacks models.
- To require the understanding how to balance security, privacy, and real-time detection in IIoT systems to stumble the required needs of industrial applications and executive standards.
- The existing research struggle in developing that anomaly detection systems those who not only secure and efficient but also amicable in privacy within IIoT networks.

2.7 Summary

This chapter delves into the federated learning methodologies applied in machine learning and network security, highlighting their applicability in improving privacy, security, and efficiency in industrial environments. Section 2.1 explores different techniques for combining FL with edge computing, blockchain, and differential privacy, aiming to tackle hurdles related to data privacy, scalability, and robustness against attacks. Section 2.2 provides extensive background on how federated learning and secure computing are utilized in IoT networks, manufacturing, smart buildings, and cybersecurity. In Section 2.3, a review of research papers highlights the development of federated secure computing systems and their client-server structure designed to separate industrial logic from cryptographic protocols, thus assuring data privacy. Section 2.4 offers a detailed investigation of existing techniques, focusing on federated secure computing and its productiveness in securing privacy while pinpointing issues related to combination and performance against different environments. The literature review summary in Section 2.5 arrange the findings into a structured table, and Section 2.6 identifies research gaps, such as the need for more robust federated learning models for IIoT and improved anomaly detection capabilities.

Chapter 3: Methodology

3.1 Data collection

In this investigate strategy, we show Edge-IIoTset dataset, expecting to back machine learning-based interruption location frameworks in (IoT) and (IIoT) operation. The dataset bolsters both centralized and FL organized, misusing a difference of advanced advances. Our technique grasps a few basic stages, from dataset and assault impersonation to show preparing, assessment, and sending, all pointed at pinpoint the security riddles confronted by IoT and IIoT systems. The Edge-IIoTset dataset imagine a comprehensive IIoT environment that join seven layers, depicting distinctive levels of usefulness in an IoT framework. These layers incorporate Cloud Computing, Organize Capacities Virtualization (NFV), Blockchain Systems, Mist Computing, Software-Defined Organizing (SDN), Edge Computing, and the IoT/IIoT Discernment Layer. Every layer plays an fundamental part in cultivating information collection and communication between devices. In each of these layers, cutting-edge advances are locked in to duplicate real-world IoT and IIoT applications. IoT and IIoT information are produced employing a wide diverse of sensors, counting temperature, mugginess, water level, and heart rate sensors, which expect the sorts of gadgets utilized in mechanical applications. These sensors capture real-time natural information, guarantee that the dataset copies the complexities of genuine IoT environments. To make the dataset valuable for interruption discovery investigate, we expect a few sorts of cyber-attacks that commonly target IoT and IIoT frameworks. In add up to, 14 particular attack types are included within the dataset, wraps a wide run of security vulnerabilities. These assaults are gathered into five essential danger categories: Refusal of Benefit (DoS and DDoS), Data Gathering, Man-in-the-Middle (MitM), Infusion Assaults, and Malware. For each category, particular assault procedures are assumed within the distinctive layers of the testbed to imitate real-world cases. For occurrence, DoS assaults are focused on at the organize layer blend up">to blend up communication between gadgets, whereas Infusion assaults are expected at the application level to wanton information trades between sensors and controllers. By accepting these distinctive assault scenarios, the dataset gets to be a important asset for preparing and testing machine learning models centered on deciding these dangers.

```
Pseudocode for Dataset Creation
1: function Create_Dataset()
2:   Initialize layers: Cloud, NFV, Blockchain, Fog, SDN, Edge, Perception
3:   for each layer in Layers do
4:     Integrate sensors (temperature, humidity, water level, heart rate)
5:     Capture real-time data
6:   end for
7:   Simulate_attack_types: DoS, DDoS, MitM, Injection, Malware
8:   for each attack in attack_types do
9:     Simulate attack on relevant layer
10:  end for
11:  return Edge-IIoTset dataset
12: end function
```

3.2 Data Preprocessing and Feature Scaling

Before using data in machine learning models, it must be preprocessed to assure compatibility and efficient in examination. One significant manner of preprocessing is features scaling, which assure that all features have a uniform scale. This step is especially important because IoT devices generate data in different units (e.g., temperature in Celsius, humidity in percentage), and disparity in feature ranges can unfavorably impact the exhibition of machine learning models. We perform feature scaling using normalization techniques. Figure the mean and standard deviation for each feature. Feature scaling assure that each feature distributed equally to the analysis by standardizing the range of the features. The local mean for each feature j in the dataset is calculated to understand the average value of that feature across all samples. First, the raw data is cleaned and check the missing values but no missing values found during the process. Category columns such as Attack_Type converted to numbers using label coding. Converted the Attack_type column with categories mapped as:Backdoor = 0, DDoS_HTTP = 1, DDoS_ICMP = 2, DDoS_TCP = 3, DDoS_UDP = 4, Fingerprinting = 5, MITM = 6, Normal = 7, Password = 8, Port_Scanning = 9, Ransomware = 10, SQL_injection = 11, Uploading = 12, Vulnerability_scanner = 13, XSS = 14. To standardize feature scales and improve model output, Z-score normalization was applied to all

input functions, and the target columns were excluded to obtain the importance of the original values. This preprocessing step confirm that the dataset is ready for machine learning algorithms. The data records strategically split to improve the training and evaluation of the model. Subjects 70% (3,327,801 samples), Validation (713,100 samples), Test (713.101 samples)15% (713,100 samples), Subjects 15% (713,1100 samples). To relate the real-world IIOT environment where data distributions differently between devices, the training set was distributed under 15 clients in a non-IID (non-independent) type, with each client receive approximately 221,853 samples. This non-IID partition introduced variability in the distribution of attacks per customer (for example, customers may be subject to more DDOS attacks, but may be included in another example of malware). Validation rates and test rates were used to monitor model flash and final performance of the model. This processing and dataset distribution approach confirm a realistic data protection-related structure for training and detection model evaluation for federation detection in IIOT networks. The local mean for each feature j is calculated as

Equation 1: Local Mean Calculation:

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} X_{ij}$$

(X_{ij}) represents the value of the (j^{th}) feature for the (i^{th}) sample. (n) show number of samples. (μ_j) is the mean of feature (j), and it helps to center the data by moving it such that the mean becomes 0 during scaling. This step figures the average of a feature against all samples in a dataset. It is critical for centering the data, which assure that features assist equally in model training process.

The local standard deviation of feature j is computed to measure the dispersal or spread of values around the mean. Also, the local standard deviation for each feature j is given by:

Equation 2: Local Standard Deviation Calculation:

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{ij} - \mu_j\right)^2}$$

(μ_j) is the local mean of feature (j), calculated from the previous step. (X_{ij}) is the value of feature (j) for sample (i). (σ_j) calibrate how much the values of feature (j) deviate from its mean. This

step helps to scale the data by assuring that the propagate of each feature is uniform. Standard deviation gives a measure of variability in the dataset.

Each feature (X_{ij}) is standardized using its local mean (μ_j) and standard deviation (σ_j) to create a scaled version of the feature.

Equation 3: Standardization (Feature Scaling) Formula

$$X_{ij}^{\text{scaled}} = \frac{X_{ij} - \mu_j}{\sigma_j}$$

(μ_j) and (σ_j) are the mean and standard deviation of the (j^{th}) feature. The result is a scaled feature (X_{ij}^{scaled}), which typically has a mean μ and standard deviation. By standardizing the feature, this step assure that all features have the same scale, making them more parallel. This show features with large numerical ranges from dominating the learning algorithm.

When multiple nodes or distributed data sources are used, the global mean across all nodes for feature (j) is measured as a weighted average of local means. To join global scaling parameters against multiple nodes:

Table 2: Z-Score Normalization on Features

No.	Feature Name	Mean Formula	Standard Deviation Formula	Standardization Formula
—	Generic Formula	$\mu_j = \frac{1}{n}\sum_{i=1}^{n} X_{ij}$	$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{ij} - \mu_j)^2}$	$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j}$
1	tcp.len	$\mu_{\text{tcp.len}} = \frac{1}{n}\sum_{i=1}^{n} tcp.len_i$	$\sigma_{\text{tcp.len}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(tcp.len_i - \mu_{\text{tcp.len}})^2}$	$Z_{\text{tcp.len}_i} = \frac{tcp.len_i - \mu_{\text{tcp.len}}}{\sigma_{\text{tcp.len}}}$
2	udp.time_delta	$\mu_{\text{udp.time\_delta}} = \frac{1}{n}\sum_{i=1}^{n} udp.time$	$\sigma_{\text{udp.time\_delta}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(udp.time\_delta_i -$	$Z_{\text{udp.time\_delta}_i} = \frac{udp.time\_delta_i - \mu_{\text{u}}}{\sigma_{\text{udp.time\_delt}}}$

3	icmp.seq_le	$\mu_{\text{icmp.seq\_le}} = \frac{1}{n}\sum_{i=1}^{n} i\,cmp.seq$	$\sigma_{\text{icmp.seq\_le}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(icmp.seq\_le_i - \mu_{\text{icm}}}$	$Z_{\text{icmp.seq\_le}_i} = \frac{icmp.seq\_le_i - \mu_{\text{icmp.s}}}{\sigma_{\text{icmp.seq\_le}}}$
4	mqtt.len	$\mu_{\text{mqtt.len}} = \frac{1}{n}\sum_{i=1}^{n} m\,qtt.len$	$\sigma_{\text{mqtt.len}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(mqtt.len_i - \mu_{\text{mqtt.le}}}$	$Z_{\text{mqtt.len}_i} = \frac{mqtt.len_i - \mu_{\text{mqtt.len}}}{\sigma_{\text{mqtt.len}}}$
5	dns.qry.name.len	$\mu_{\text{dns.qry.name.len}} = \frac{1}{n}\sum_{i=1}^{n} d\,ns.qry.$	$\sigma_{\text{dns.qry.name.len}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(dns.qry.name.len_i}$	$Z_{\text{dns.qry.name.len}_i} = \frac{dns.qry.name.len_i -}{\sigma_{\text{dns.qry.nam}}}$

Pseudocode for Preprocessing

```
1: function Preprocess_Data(dataset)
2:   for each feature in dataset do
3:     Compute local mean μ_j = (1/n) * sum(X_ij)
4:     Compute local variance σ_j^2 = (1/n) * sum((X_ij - μ_j)^2)
5:     for each X_ij in feature do
6:       Normalize: X_ij_scaled = (X_ij - μ_j) / sqrt(σ_j^2 + ε)
7:     end for
8:   end for
9:   if Federated Learning then
10:    Compute global mean μ_global,j and global variance σ_global,j^2
11:  end if
12:  return scaled dataset
13: end function
```

3.3 Federated Learning Structure:

Federated Learning (FL) is a decentralized machine learning approach in which different edge devices collaboratively prepare a global model without sending raw data. In this think about, we apply FL to improve anomaly things in IIoT systems whereas protecting information security. The design consists of a central server planning the training process and numerous clients (IIoT devices) holding local datasets. Each client trains a local LSTM-based model on its information and sends only model updates (gradients) to the server, guaranteeing sensitive data remains on device. The server aggregates these model parametrs using Federated Averaging (FedAvg) to refine a global model, which is then redistributed to clients for further training. This iterative handle proceeds for 10 global communication rounds, adjusting model performance and privacy. Key focal points include decreased communication overhead, compliance with information controls (e.g., GDPR), and flexibility to heterogeneous IIoT environments.

Federated Learning and Local Model Training: LSTM Model Structure

The center of our FL system is a 3-layer LSTM neural network optimized for sequential IIoT traffic information. The model comprises 128 hidden units per LSTM layer, taken after by ReLU activation to capture non-linear patterns in network behavior. Input measurements adjust with the 61 preprocessed features, and the output layer classifies 15 attack types (counting normal traffic). The LSTM ability to handle time-series information makes it perfect for detecting temporal anomalies (e.g., DDoS attacks). Training start locally on each client utilizing the Adam optimizer (learning rate = 0.01) and cross-entropy loss for multi-class classification. To avoid overfitting, gradients are clipped to a most extreme L2 standard of 1.0 during backpropagation. This plan guarantees proficient learning over different IIoT devices whereas keeping up low computational overhead for resource-constrained edge nodes.

Federated Learning and Local Model Training: Local Training with Gradient Clipping

Local training is done on each device processes approximately 221,853 samples per client, with batch size 2024 processing to refine memory usage. The training integrates the preprocessed and normalized features while preserving the categorical encoding of attack types. After each round of local training, devices only transmit model parameter updates without raw data, significantly reducing communication overhead compared to centralized approaches. The server aggregates these updates using a weighted average based on the amount of data each client possesses, creating an improved global model that is then redistributed to all participants.

Federated Averaging with Differential Privacy: Gaussian Noise

Privacy preservation is implemented through different instruments during the federated training process. Differential security procedures are applied amid model aggregation, where carefully calibrated noise is added to the model updates before averaging. This ensures individual device information cannot be induced from the shared gradients. The federated averaging handle runs for 10 global communication rounds, with each round including parallel local training over devices taken after by secure aggregation of model parameters. The non-IID distribution of information across clients is intentioned maintained to reflect real-world IIoT scenarios where different devices may experience distinctive attack patterns or normal behavior profiles. This updated global model will be used in the next training round. The update rule is:

Equation 4: Federated learning with Gaussian Noise

$$w_{global} = \frac{1}{N}\sum_{i=1}^{N} w_i + \mathcal{N}(0, \sigma^2)$$

Here, w_i are the local model weights from each of the N clients, and $\mathcal{N}(0, \sigma^2)$ represents Gaussian noise. After aggregation, the global model is redistributed to clients for the next training round. This approach enables collaborative learning across decentralized IIoT nodes while preserving data privacy, robustness, and scalability.

Given the dispense nature of IoT and IIoT environments, Federated Learning (FL) is an ideal approach for training models locally on edge devices without giving sensitive data with a central server. FL allows for model updates to be joined from multiple devices, refining the global model without direct access to local datasets. Nevertheless, this method introduces privacy concerns, which we address by implementing Differential Privacy (DP) and Secure Federated Averaging (SFA). In each local device, the model parameters (w_k) are updated using the local data, but to protect user privacy, Gaussian noise is added to the model updates:

```
Pseudocode for Federated Training
1: function Federated_Learning_Setup()
2:   for each device k do
3:     Train local model w_k = Train_LSTM(X_k, y_k)
4:     Add Differential Privacy: w_k_DP = w_k + Gaussian_noise(0, σ^2)
```

```
    Encrypt model updates: w_k_enc = Encrypt(w_k_DP)
end for
Aggregate encrypted updates at server:
w_global_enc = Sum(w_k_enc for k = 1 to K) / Sum(n_k for k = 1 to K)
Decrypt global model: w_global = Decrypt(w_global_enc)
return global model w_global
end function
```

3.4 Model Aggregation

For model training, we train models using a federated learning method, where data from all devices and layers are send to central server for model training. We aim to understand the trade-offs between performance and privacy. The model aggregation process in federated learning system follows a carefully designed protocol to combine local model updates while maintaining privacy and improving detection accuracy. When each client completes its local training on the non-IID distributed data, the central server initiates the aggregation step using Federated Averaging (FedAvg). The server receives encrypted model parameters - specifically the weights and gradients from all participating IIoT devices. Each client's work is weighted based on the size of its local dataset, assure devices with more samples have proportionally greater influence on the global model update. Before aggregation, differential privacy techniques are applied by adding carefully calibrated Gaussian noise to the received parameters, providing strong privacy guarantees against potential inference attacks while maintaining model utility.

The aggregation algorithm computes a weighted average of all received model updates, where the weighting factors correspond to the relative sizes of each client's training subset. This approach helps mitigate biases that might arise from uneven data distributions across devices. The server then applies additional security measures including gradient clipping and noise addition to further protect sensitive information before updating the global model. The newly aggregated global model undergoes validation using the reserved validation set to assess performance improvements before being redistributed to all clients for the next training round. This iterative process continues for the predefined 10 communication rounds, with each cycle progressively refining the model's ability to detect various attack types while preserving the privacy of each device's local data.

Key innovations in this aggregation process include adaptive weighting for non-IID data distributions and dynamic noise scaling that automatically adjusts based on the model's convergence behavior. The system also implements mechanisms to detect and handle potential malicious updates or byzantine failures that might occur in industrial environments. By combining these techniques, the aggregation phase achieves an optimal balance between learning from diverse IIoT devices and protecting sensitive operational data, ultimately producing a robust global anomaly detection model without requiring centralized data collection. The final aggregated model demonstrates improved generalization across different attack scenarios while maintaining compliance with strict industrial privacy requirements.

Pseudocode for Model Aggregation in Federated Learning

```
function Aggregate_Models(devices)
  Initialize global model: w_global
  Initialize learning rate: α
  while training continues do
    ∇L_global = 0  // Initialize global gradient
    n_total = 0     // Total sample count
    for each device k in devices do
      ∇L_k = Compute_Gradient(Loss(X_k, y_k, w_k), w_k)  // Compute local gradient
      ∇L_global += n_k * ∇L_k  // Weighted sum of gradients
      n_total += n_k  // Accumulate total samples
    end for
    ∇L_global /= n_total  // Normalize global gradient
    w_global = w_global - α * ∇L_global  // Update global model
  end while
  return w_global  // Return updated global model
end function
```

3.5 Global Model Evaluation: Evaluation Metrics

Once the models are trained, their performance is evaluated using different machine learning metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics help estimate the model's ability to correctly identify threats and minimize false positives.

The accuracy is calculated as:

Equation 5: Accuracy

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

The precision is calculated as:

Equation 6: Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

where TP show number of true positives and FP show number of false positives. Recall is similarly computed as:

Equation 7: Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

where FN represents the false negatives. The F1-score provides a balance between precision and recall:

Equation 8: F1-Score

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

In addition, the ROC-AUC metric assesses the balance between true positives and false positives across different threshold settings.

Equation 9: ROC-AUC

$$\text{ROC-AUC} = \int_0^1 \text{TPR}(t)\ d\text{FPR}(t)$$

Calculate how much the true positive changes as the false positive changes by combining the FPR between 0 and 1. Measuring the performance of a global model using metrics such as accuracy, precision, recall, F1 score, and ROC-AUC helps evaluate the effectiveness of the model in identifying patterns. It is necessary to balance the good with the bad, but also to consider the

threats. This step is essential for building effective and efficient models in distributed IoT/IIoT environments where privacy and security are of utmost importance.

Equation 10: False Acceptance Rate (FAR)

The False Acceptance Rate (FAR) measures how often an incorrect (unauthorized/malicious) sample is wrongly accepted as legitimate. It is calculated as:

$$\text{FAR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

where FP = False Positives (incorrectly accepted), TN = True Negatives (correctly rejected).

A lower FAR indicates better security, as fewer unauthorized accesses are permitted.

Equation 11: False Negative Rate (FNR)

The False Negative Rate (FNR) measures how often a legitimate (authorized/normal) sample is incorrectly rejected as malicious. It is calculated as:

$$\text{FNR} = \frac{\text{FN}}{\text{TP} + \text{FN}}$$

where FN = False Negatives (missed threats), TP = True Positives (correctly detected threats).

A lower FNR indicates better detection reliability, as fewer legitimate instances are wrongly flagged.

Equation 12: Response Time

The Response Time measures the time taken by the model to process an input and return a decision. It is critical in real-time IoT/IIoT systems where delays can impact security and efficiency.

$$\text{Response Time} = T_{\text{processing}} + T_{\text{transmission}}$$

where:

- $T_{\text{processing}}$ = Time for model inference
- $T_{\text{transmission}}$ = Network/data transfer delay

Lower response times improve system performance, especially in time-sensitive applications.

Balancing these metrics ensures a robust, efficient, and secure model deployment in distributed environments.

3.6 Continuous Monitoring and Comparison:

In my research, I take a comprehensive evaluation of nine machine learning and deep learning models to address the most effective approach for detecting cyber threats in IoT environments, using the Edge-IIoTset dataset. The models I compared include traditional machine learning

methods such as Logistic Regression, Ridge Classifier, SGD Classifier, Bernoulli Naive Bayes, and Linear Discriminant Analysis (LDA), as well as more advanced neural network architectures like Multilayer Perceptron (MLP) and Feedforward Neural Networks (Feedforward NN). Additionally, I explored specialized techniques like Growing Neural Gas (GNG) and Conditional Random Fields (CRF), though these were implemented using simplified placeholders (KMeans for GNG and Logistic Regression for CRF) due to their complexity. The focus of this comparison was to assess each model's ability to handle the high-dimensional, imbalanced, and dynamic nature of IoT security data while balancing results metrics such as accuracy, precision, recall, and computational efficiency. Key parameters evaluated included training time, false alarm rates (FAR), false negative rates (FNR), and the ability to generalize across training, validation, and test sets. This analysis aimed to highlight the strengths and limitations of each model in real-world IoT threat detection scenarios, where scalability, privacy, and real-time processing are critical. The Federated LSTM model, which I propose as a superior alternative, was later introduced to address the limitations of these centralized approaches by leveraging distributed training across edge devices without compromising data privacy. The comparative study provided a baseline to demonstrate why Federated LSTM outperforms traditional and deep learning models in terms of accuracy, adaptability, and efficiency, making it the optimal choice for securing decentralized IoT ecosystems.

System Architecture Diagram:

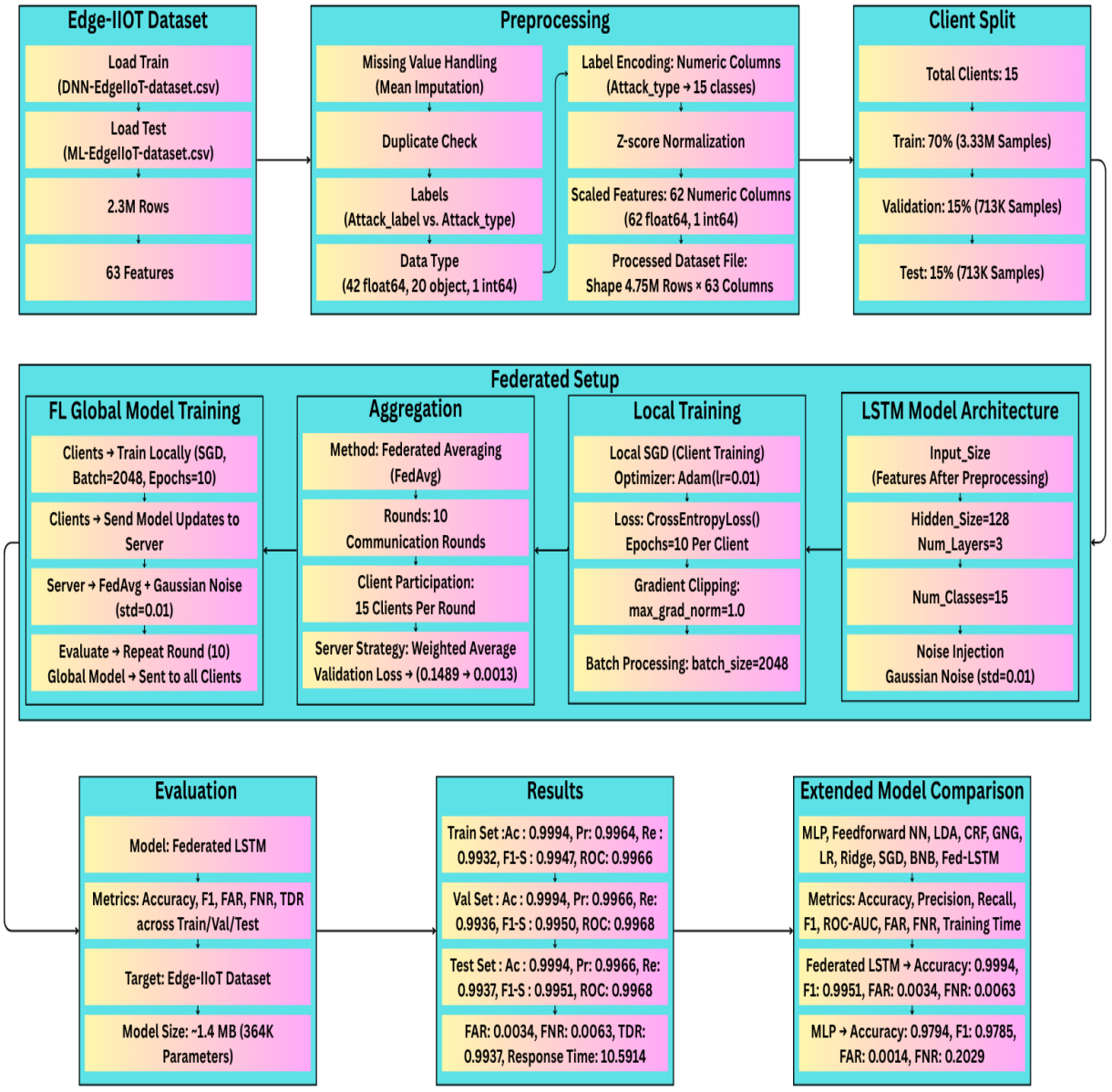

Figure 3. 1 System Architecture Diagram

This Architecture Diagram appear the stream of information and operations in a FL framework for anomaly location in (IoT) and (IIoT) situations. The method begins with nearby show preparing on each gadget, where information is collected and preprocessed. Nearby models are at that point overhauled and conveyed to a central server for combination. This combination step upgrades a global model based on the accumulated data from all gadgets. Peculiarity discovery is at that point

performed on the global model and input is conveyed back to the gadgets for encourage enhancement. At last, the framework applies security measures to secure protection and guarantee ceaseless observing and improvement of the sent show. This approach leverages the control of conveyed learning, where person gadgets contribute to a shared information base, whereas ensuring delicate information and adjusting to advancing dangers in energetic IoT systems.

3.7 Summary

In this chapter we show the Edge-IIoTset dataset, made to upgrade ML based intrusion detection frameworks for IoT and IIoT situations. The dataset includes seven useful layers, counting Cloud Computing and Edge Computing, to mimic real-world applications utilizing differing sensors. It retains 14 diverse cyber-attack sorts over five danger categories, indicating basic security vulnerabilities in IoT frameworks. The chapter subtle elements the technique for preprocessing information through highlight scaling and locks in unified learning, permitting model preparing on edge gadgets whereas securing client security through methods like Differential Security and Secure Federated Averaging. It moreover diagrams the preparing prepare for nearby models, demonstrate accumulation, execution measure through measurements like exactness and F1-score. Ceaseless observing and enhancement of the demonstrate are helped through real-time input from IIoT gadgets, empowering versatile reactions to advancing conditions.

Chapter 4: Experimental Setup

Taking after the foundation of the Edge-IIoTset dataset and the point by point technique locked in for preparing and analyzing machine learning models, we show the comes about picked up from our tests. The measured measurements find imperative bits of knowledge into the viability of our intrusion detection frameworks against distinctive arrangements and assault scenarios. Each show was surveyed based on its capacity to precisely classify assaults whereas minimizing wrong positives, showing the dataset's productivity and flexibility. We'll dig into particular discoveries with respect to exactness, accuracy, review, and F1-score for each of the 14 assault sorts included within the dataset. Furthermore, we investigate how federated learning approaches, joined with privacy-preserving components, decided show execution and flexibility in real-time situations. The subsequent sections will provide an extensive analysis of these results, illustrating the practical suggestions of our research for enhancing security measures in IOT and IIoT applications.

4.1 Edge-IIoTset Dataset

We use a new global realistic cyber security dataset of IoT and IIoT applications, called Edge-IIoTset, which can be used by ML based intrusion detection systems in two different modes, namely, centralized and FL. Mainly, the given testbed is arranged into seven layers, including, Cloud Computing Layer, Network Functions Virtualization Layer, Blockchain Network Layer, Fog Computing Layer, Software-Defined Networking Layer, Edge Computing Layer, and IoT and IIoT Perception Layer. In every layer, we show new emerging technologies that satisfy the key requirements of IoT and IIoT applications, such as, Things Board IoT platform, OPNFV platform, Hyperledger Sawtooth, Digital twin, ONOS SDN controller, Mosquitto MQTT brokers, Modbus TCP/IP, …etc. The IoT data are produced from many IoT devices (more than 10 types) like Low-cost digital sensors for sensing temperature and humidity, Ultrasonic sensor, Water level detection sensor, pH Sensor Meter, Soil Moisture sensor, Heart Rate Sensor, Flame Sensor, …etc.). However, we point and analyze fourteen attacks related to IoT and IIoT connectivity protocols, which are categorized into five threats, including, DoS/DDoS attacks, Information gathering, Man in the middle attacks, Injection attacks, and Malware attacks. After testing and proceeding the proposed realistic cyber security dataset, we provide a primary investigative data analysis and evaluate the performance of machine learning approaches in both centralized and federated learning modes.

The simulation setup and parameters for the proposed anomaly detection system in (IIoT) networks encompass a embrace multi-step process aimed at combining, preprocessing, training, aggregating, evaluating, and attest the privacy and security of the anomaly detection structure. Initially, data collection points on accessing related information from different industrial sources, including sensors, machinery logs, and network traffic, absorbing datasets like Edge-IIoTset for testing and training. The ensuing data preprocessing step includes meticulous cleaning, transformation, and normalization techniques to handle challenges such as noise, missing values, and differing formats. Federated learning setup follows, separating data for cooperative training while preserving decentralization and privacy using methods like Federated Averaging and Secure Aggregation. Local Model Training allows unique devices to train anomaly detection models using techniques like LSTM algorithms, ensuring privacy and exploiting device-specific insights. Model Aggregation then joined locally trained models securely using techniques like Federated Averaging and Secure Multiparty Computation. Global Model Evaluation assesses the aggregated model's performance using metrics like Precision, Recall, F1-Score, and ROC-AUC. Privacy and Security Analysis scrutinizes the system's safeguards like differential privacy and encryption. Model Deployment integrates the trained global model onto IIoT devices for real-time anomaly detection, while Continuous Monitoring and Improvement iteratively refines the model based on real-world feedback to consolidate its accuracy and efficiency over time.

4.1.1 Accuracy

Accuracy is one of the foremost essential execution measurements and appear the portion of accurately classified occasions among all occurrences. It's measured proportion of number of correct forecasts to whole number of predictions. While accuracy is basic to get it, it may not be the most excellent metric for imbalanced datasets where one lesson rules the others.

Accuracy = (TP + TN) / (TP + TN + FP + FN)……...(1)

4.1.2 F1 Score

The F1 score is consonant cruel of precision and review. It gives a adjust between exactness and review. F1 score is valuable when we got to look for a adjust between accuracy and review, particularly when there's an uneven lesson distribution.

F1 Score = 2 * ((Precision * Recall) / (Precision + Recall))……...…(2)

4.1.3 Precision

Precision may be a execution metric utilized to assess the exactness of a classification demonstrate, particularly for double classification tasks. Precision is regularly considered along with review (the fitness of the demonstrate to discover all related cases interior a dataset). Exactness focuses on the quality of positive forecasts, review centers on the fitness to induce all positive situation.

Precision = TP / (TP + FP)……..….(3)

4.1.4 Recall

Recall is the proportion of genuine positive expectations to the whole number of real positive occurrences (genuine positives and wrong negatives). It calculate the model's capacity to accurately recognize all positive occasions. Review is imperative when the taken a toll of wrong negatives is high.

Recall = TP / (TP + FN)……..…(4)

4.1.5 ROC-AUC

Receiver Operating Characteristic (ROC) bend may be a plot of the genuine positive rate against the untrue positive rate. The zone beneath the ROC bend (ROC-AUC) gives a single scalar esteem speaking to the model's execution over all classification edges. It's particularly valuable for imbalanced datasets.

AUC-ROC=$\sum_{(i=1)}^{(N-1)}(1/2)(FPRi+1-FPRi)\times(TPRi+1+TPRi)$……..…(5)

4.2 Results

4.2.1 Data Collection

To optically represent the disbursement of attack labels and types in the Edge-IIoTset dataset, we used a combination of training and testing data. The dataset includes both normal example and malicious activities categorized into different attack types, they are difficult for training and analyzing intrusion detection models. The results, as shown in Figure 4.1, instance the frequency and distribution of different attack types against the training and testing datasets. The two subplots in Figure 4.1 provide insight into the data model. The second plot represents the training data, displaying the various attack labels and how they are distributed among the different attack types. Similarly, the first plot shows the distribution for the test data. These vision are needed for

understanding the balance of the dataset and decide if any attack types are over or under-represented, which could impact model performance.

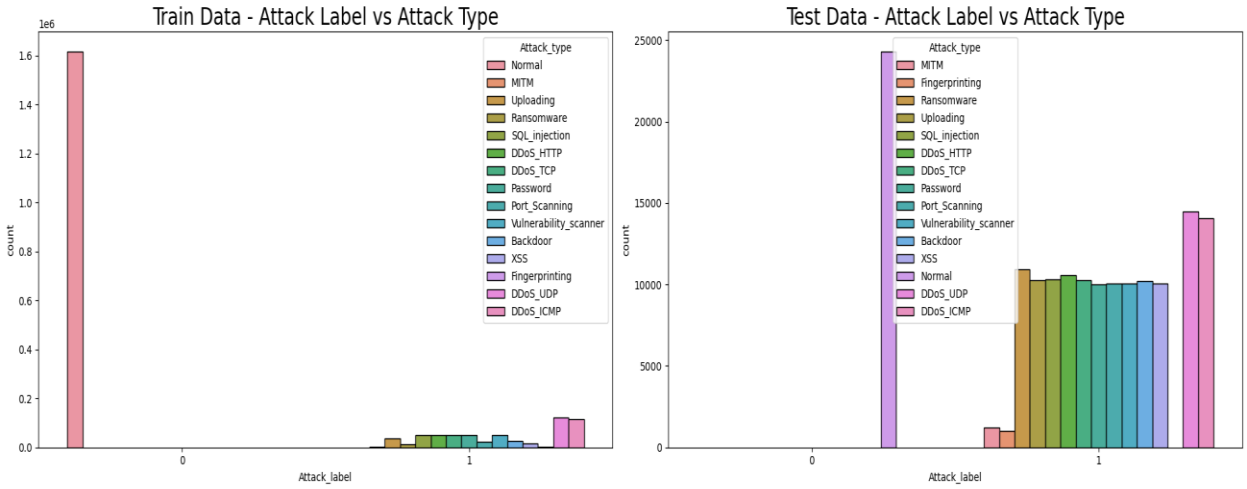

Figure 4. 1: Attack Label vs Attack Type in Train and Test Data

4.2.2 Data Preprocessing and Feature Scaling

The process begins by importing two key cybersecurity datasets - one dataset for training deep learning models and another for testing machine learning models. Before any processing occurs, we first check samples from each dataset to ensure both loaded complete. This initial check looks at the first few records and reviews basic structural information including column names, data types, and memory usage. This step is crucial to clear any immediate issues with data quality or formatting.

```
First 10 rows of the train data:
                 frame.time    ip.src_host    ip.dst_host arp.dst.proto_ipv4  \
0   2021 11:44:10.081753000   192.168.0.128  192.168.0.101                   0
1   2021 11:44:10.162218000   192.168.0.101  192.168.0.128                   0
2   2021 11:44:10.162271000   192.168.0.128  192.168.0.101                   0
3   2021 11:44:10.162641000   192.168.0.128  192.168.0.101                   0
4   2021 11:44:10.166132000   192.168.0.101  192.168.0.128                   0
5   2021 11:44:10.166159000   192.168.0.128  192.168.0.101                   0
6   2021 11:44:10.166968000   192.168.0.101  192.168.0.128                   0
7   2021 11:44:10.167072000   192.168.0.128  192.168.0.101                   0
8   2021 11:44:10.169612000   192.168.0.101  192.168.0.128                   0
9   2021 11:44:10.169644000   192.168.0.128  192.168.0.101                   0

   arp.opcode  arp.hw.size arp.src.proto_ipv4  icmp.checksum  icmp.seq_le  \
0         0.0          0.0                  0            0.0          0.0
1         0.0          0.0                  0            0.0          0.0
2         0.0          0.0                  0            0.0          0.0
3         0.0          0.0                  0            0.0          0.0
4         0.0          0.0                  0            0.0          0.0
5         0.0          0.0                  0            0.0          0.0
6         0.0          0.0                  0            0.0          0.0
7         0.0          0.0                  0            0.0          0.0
8         0.0          0.0                  0            0.0          0.0
9         0.0          0.0                  0            0.0          0.0

   icmp.transmit_timestamp  ...  mqtt.proto_len mqtt.protoname  \
0                      0.0  ...             0.0              0
1                      0.0  ...             4.0           MQTT
2                      0.0  ...             0.0              0
3                      0.0  ...             0.0              0
4                      0.0  ...             0.0              0
5                      0.0  ...             0.0              0
6                      0.0  ...             0.0              0
7                      0.0  ...             0.0              0
8                      0.0  ...             0.0              0
9                      0.0  ...             0.0              0

                mqtt.topic mqtt.topic_len mqtt.ver mbtcp.len mbtcp.trans_id  \
0                        0            0.0      0.0       0.0            0.0
1                        0            0.0      4.0       0.0            0.0
2                        0            0.0      0.0       0.0            0.0
3                        0            0.0      0.0       0.0            0.0
4  Temperature_and_Humidity           24.0      0.0       0.0            0.0
5                        0            0.0      0.0       0.0            0.0
6                        0            0.0      0.0       0.0            0.0
7                        0            0.0      0.0       0.0            0.0
8                        0            0.0      0.0       0.0            0.0
9                        0            0.0      0.0       0.0            0.0

  mbtcp.unit_id  Attack_label  Attack_type
0           0.0             0       Normal
1           0.0             0       Normal
2           0.0             0       Normal
3           0.0             0       Normal
4           0.0             0       Normal
5           0.0             0       Normal
6           0.0             0       Normal
7           0.0             0       Normal
8           0.0             0       Normal
9           0.0             0       Normal

[10 rows x 63 columns]
```

Figure 4. 2: Train Dataset Rows Information

```
rain Data Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2219201 entries, 0 to 2219200
Data columns (total 63 columns):
 #   Column                      Dtype
---  ------                      -----
 0   frame.time                  object
 1   ip.src_host                 object
 2   ip.dst_host                 object
 3   arp.dst.proto_ipv4          object
 4   arp.opcode                  float64
 5   arp.hw.size                 float64
 6   arp.src.proto_ipv4          object
 7   icmp.checksum               float64
 8   icmp.seq_le                 float64
 9   icmp.transmit_timestamp     float64
 10  icmp.unused                 float64
 11  http.file_data              object
 12  http.content_length         float64
 13  http.request.uri.query      object
 14  http.request.method         object
 15  http.referer                object
 16  http.request.full_uri       object
 17  http.request.version        object
 18  http.response               float64
 19  http.tls_port               float64
 20  tcp.ack                     float64
 21  tcp.ack_raw                 float64
 22  tcp.checksum                float64
 23  tcp.connection.fin          float64
 24  tcp.connection.rst          float64
 25  tcp.connection.syn          float64
 26  tcp.connection.synack       float64
 27  tcp.dstport                 float64
 28  tcp.flags                   float64
 29  tcp.flags.ack               float64
 30  tcp.len                     float64
 31  tcp.options                 object
 32  tcp.payload                 object
 33  tcp.seq                     float64
 34  tcp.srcport                 object
 35  udp.port                    float64
 36  udp.stream                  float64
 37  udp.time_delta              float64
 38  dns.qry.name                float64
 39  dns.qry.name.len            object
 40  dns.qry.qu                  float64
 41  dns.qry.type                float64
 42  dns.retransmission          float64
 43  dns.retransmit_request      float64
 44  dns.retransmit_request_in   float64
 45  mqtt.conack.flags           object
 46  mqtt.conflag.cleansess      float64
 47  mqtt.conflags               float64
 48  mqtt.hdrflags               float64
 49  mqtt.len                    float64
 50  mqtt.msg_decoded_as         float64
 51  mqtt.msg                    object
 52  mqtt.msgtype                float64
 53  mqtt.proto_len              float64
 54  mqtt.protoname              object
 55  mqtt.topic                  object
 56  mqtt.topic_len              float64
 57  mqtt.ver                    float64
 58  mbtcp.len                   float64
 59  mbtcp.trans_id              float64
 60  mbtcp.unit_id               float64
 61  Attack_label                int64
 62  Attack_type                 object
dtypes: float64(42), int64(1), object(20)
memory usage: 1.0+ GB
None
```

Figure 4. 3: Train Dataset Structure Information

```
est Data Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 157800 entries, 0 to 157799
Data columns (total 63 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   frame.time                  157800 non-null  object
 1   ip.src_host                 157800 non-null  object
 2   ip.dst_host                 157800 non-null  object
 3   arp.dst.proto_ipv4          157800 non-null  object
 4   arp.opcode                  157800 non-null  float64
 5   arp.hw.size                 157800 non-null  float64
 6   arp.src.proto_ipv4          157800 non-null  object
 7   icmp.checksum               157800 non-null  float64
 8   icmp.seq_le                 157800 non-null  float64
 9   icmp.transmit_timestamp     157800 non-null  float64
 10  icmp.unused                 157800 non-null  float64
 11  http.file_data              157800 non-null  object
 12  http.content_length         157800 non-null  float64
 13  http.request.uri.query      157800 non-null  object
 14  http.request.method         157800 non-null  object
 15  http.referer                157800 non-null  object
 16  http.request.full_uri       157800 non-null  object
 17  http.request.version        157800 non-null  object
 18  http.response               157800 non-null  float64
 19  http.tls_port               157800 non-null  float64
 20  tcp.ack                     157800 non-null  float64
 21  tcp.ack_raw                 157800 non-null  float64
 22  tcp.checksum                157800 non-null  float64
 23  tcp.connection.fin          157800 non-null  float64
 24  tcp.connection.rst          157800 non-null  float64
 25  tcp.connection.syn          157800 non-null  float64
 26  tcp.connection.synack       157800 non-null  float64
 27  tcp.dstport                 157800 non-null  float64
 28  tcp.flags                   157800 non-null  float64
 29  tcp.flags.ack               157800 non-null  float64
 30  tcp.len                     157800 non-null  float64
 31  tcp.options                 157800 non-null  object
 32  tcp.payload                 157800 non-null  object
 33  tcp.seq                     157800 non-null  float64
 34  tcp.srcport                 157800 non-null  object
 35  udp.port                    157800 non-null  float64
 36  udp.stream                  157800 non-null  float64
 37  udp.time_delta              157800 non-null  float64
 38  dns.qry.name                157800 non-null  float64
 39  dns.qry.name.len            157800 non-null  object
 40  dns.qry.qu                  157800 non-null  float64
 41  dns.qry.type                157800 non-null  float64
 42  dns.retransmission          157800 non-null  float64
 43  dns.retransmit_request      157800 non-null  float64
 44  dns.retransmit_request_in   157800 non-null  float64
 45  mqtt.conack.flags           157800 non-null  object
 46  mqtt.conflag.cleansess      157800 non-null  float64
 47  mqtt.conflags               157800 non-null  float64
 48  mqtt.hdrflags               157800 non-null  float64
 49  mqtt.len                    157800 non-null  float64
 50  mqtt.msg_decoded_as         157800 non-null  float64
 51  mqtt.msg                    157800 non-null  object
 52  mqtt.msgtype                157800 non-null  float64
 53  mqtt.proto_len              157800 non-null  float64
 54  mqtt.protoname              157800 non-null  object
 55  mqtt.topic                  157800 non-null  object
 56  mqtt.topic_len              157800 non-null  float64
 57  mqtt.ver                    157800 non-null  float64
 58  mbtcp.len                   157800 non-null  float64
 59  mbtcp.trans_id              157800 non-null  float64
 60  mbtcp.unit_id               157800 non-null  float64
 61  Attack_label                157800 non-null  int64
 62  Attack_type                 157800 non-null  object
dtypes: float64(42), int64(1), object(20)
memory usage: 75.8+ MB
None
```

Figure 4.4: Test Dataset Structure Information

After confirming both datasets loaded properly, we combine both into a single dataset file. This combined dataset contains all available cybersecurity event records from both original files. We save this combined dataset in new file, creating a master dataset that can be used for various analyses and modeling approaches. This integration ensures we have all available data in one place for more advance processing.

```
\combined Data Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2377001 entries, 0 to 2377000
Data columns (total 63 columns):
 #   Column                      Dtype
---  ------                      -----
 0   frame.time                  object
 1   ip.src_host                 object
 2   ip.dst_host                 object
 3   arp.dst.proto_ipv4          object
 4   arp.opcode                  float64
 5   arp.hw.size                 float64
 6   arp.src.proto_ipv4          object
 7   icmp.checksum               float64
 8   icmp.seq_le                 float64
 9   icmp.transmit_timestamp     float64
 10  icmp.unused                 float64
 11  http.file_data              object
 12  http.content_length         float64
 13  http.request.uri.query      object
 14  http.request.method         object
 15  http.referer                object
 16  http.request.full_uri       object
 17  http.request.version        object
 18  http.response               float64
 19  http.tls_port               float64
 20  tcp.ack                     float64
 21  tcp.ack_raw                 float64
 22  tcp.checksum                float64
 23  tcp.connection.fin          float64
 24  tcp.connection.rst          float64
 25  tcp.connection.syn          float64
 26  tcp.connection.synack       float64
 27  tcp.dstport                 float64
 28  tcp.flags                   float64
 29  tcp.flags.ack               float64
 30  tcp.len                     float64
 31  tcp.options                 object
 32  tcp.payload                 object
 33  tcp.seq                     float64
 34  tcp.srcport                 object
 35  udp.port                    float64
 36  udp.stream                  float64
 37  udp.time_delta              float64
 38  dns.qry.name                float64
 39  dns.qry.name.len            object
 40  dns.qry.qu                  float64
 41  dns.qry.type                float64
 42  dns.retransmission          float64
 43  dns.retransmit_request      float64
 44  dns.retransmit_request_in   float64
 45  mqtt.conack.flags           object
 46  mqtt.conflag.cleansess      float64
 47  mqtt.conflags               float64
 48  mqtt.hdrflags               float64
 49  mqtt.len                    float64
 50  mqtt.msg_decoded_as         float64
 51  mqtt.msg                    object
 52  mqtt.msgtype                float64
 53  mqtt.proto_len              float64
 54  mqtt.protoname              object
 55  mqtt.topic                  object
 56  mqtt.topic_len              float64
 57  mqtt.ver                    float64
 58  mbtcp.len                   float64
 59  mbtcp.trans_id              float64
 60  mbtcp.unit_id               float64
 61  Attack_label                int64
 62  Attack_type                 object
dtypes: float64(42), int64(1), object(20)
memory usage: 1.1+ GB
None
```

Figure 4.5: Combined Dataset Structure Information

With our combined dataset, we apply initial analysis focusing on the attack characteristics. Using visualization techniques, we create comparative charts showing the distribution of different attack types between the original training and test datasets. These visualizations help us understand the balance and representation of various cybersecurity threats in our data. We then generate similar visualizations for the complete merged dataset to examine the overall attack landscape.

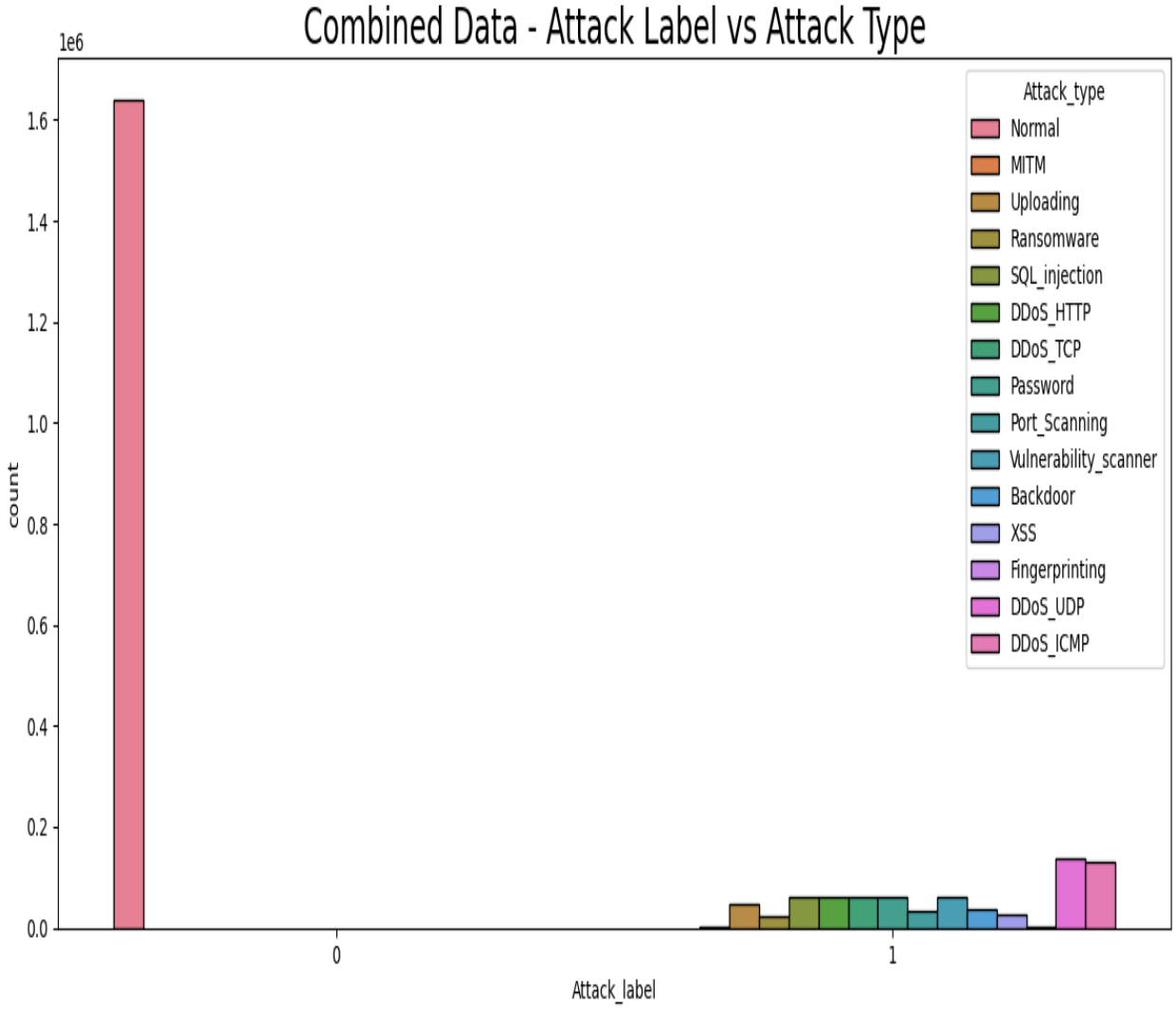

Figure 4.6: Combined Dataset Visualization Chart

To enhance our dataset's robustness, we implement a data augmentation approach by duplicating the combined dataset. This technique effectively doubles our available training examples, which can help improve machine learning model performance, particularly for detecting rare attack patterns. We save this enhanced version as a separate file to maintain data integrity throughout our experimentation process.

```
First 10 rows of the final_combined_data data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4754002 entries, 0 to 4754001
Data columns (total 63 columns):
 #   Column                      Dtype
---  ------                      -----
 0   frame.time                  object
 1   ip.src_host                 object
 2   ip.dst_host                 object
 3   arp.dst.proto_ipv4          object
 4   arp.opcode                  float64
 5   arp.hw.size                 float64
 6   arp.src.proto_ipv4          object
 7   icmp.checksum               float64
 8   icmp.seq_le                 float64
 9   icmp.transmit_timestamp     float64
 10  icmp.unused                 float64
 11  http.file_data              object
 12  http.content_length         float64
 13  http.request.uri.query      object
 14  http.request.method         object
 15  http.referer                object
 16  http.request.full_uri       object
 17  http.request.version        object
 18  http.response               float64
 19  http.tls_port               float64
 20  tcp.ack                     float64
 21  tcp.ack_raw                 float64
 22  tcp.checksum                float64
 23  tcp.connection.fin          float64
 24  tcp.connection.rst          float64
 25  tcp.connection.syn          float64
 26  tcp.connection.synack       float64
 27  tcp.dstport                 float64
 28  tcp.flags                   float64
 29  tcp.flags.ack               float64
 30  tcp.len                     float64
 31  tcp.options                 object
 32  tcp.payload                 object
 33  tcp.seq                     float64
 34  tcp.srcport                 object
 35  udp.port                    float64
 36  udp.stream                  float64
 37  udp.time_delta              float64
 38  dns.qry.name                float64
 39  dns.qry.name.len            object
 40  dns.qry.qu                  float64
 41  dns.qry.type                float64
 42  dns.retransmission          float64
 43  dns.retransmit_request      float64
 44  dns.retransmit_request_in   float64
 45  mqtt.conack.flags           object
 46  mqtt.conflag.cleansess      float64
 47  mqtt.conflags               float64
 48  mqtt.hdrflags               float64
 49  mqtt.len                    float64
 50  mqtt.msg_decoded_as         float64
 51  mqtt.msg                    object
 52  mqtt.msgtype                float64
 53  mqtt.proto_len              float64
 54  mqtt.protoname              object
 55  mqtt.topic                  object
 56  mqtt.topic_len              float64
 57  mqtt.ver                    float64
 58  mbtcp.len                   float64
 59  mbtcp.trans_id              float64
 60  mbtcp.unit_id               float64
 61  Attack_label                int64
 62  Attack_type                 object
dtypes: float64(42), int64(1), object(20)
memory usage: 2.2+ GB
None
```

Figure 4.7: Duplicate Combined Dataset Structure Information

The core data preparation phase involves several critical preprocessing steps. First, we convert all numerical data to a consistent floating-point format while handling any non-numeric values appropriately. Next, we transform all categorical text data (including attack type labels) into

numerical representations using label encoding, which creates a consistent numerical mapping for each category. This transformation is essential because machine learning algorithms require numerical input. To ensure all numerical features contribute equally to machine learning models, we standardize them using z-score normalization. This process adjusts all numerical columns to have a mean of zero and standard deviation of one, preventing features with larger scales from dominating the model training process. We carefully preserve the original attack labels during this transformation to maintain our prediction targets. Before concluding the preprocessing, we perform comprehensive validation checks on our processed data. We examine the new ranges of all normalized features, calculate their means and standard deviations to confirm proper scaling, and verify that all categorical encodings were applied correctly. These validation steps ensure our data meets all requirements for effective machine learning model training. The fully processed dataset is saved in its final form, ready for machine learning applications. We preserve all preprocessing transformations (like the label encodings and scaling parameters) to ensure consistent processing of future data. This prepared dataset now contains clean, normalized numerical features and properly encoded categorical variables, optimized for training various cybersecurity threat detection models. The next phase would involve splitting this data into training and validation sets and beginning the model development process.

```
Cell 18 Output 1:

Preview of Processed Data:
   frame.time  ip.src_host  ip.dst_host  arp.dst.proto_ipv4  arp.opcode  \
0   -1.647572     0.295688     0.431920           -0.091497   -0.052801
1   -1.647570     0.295642     0.432029           -0.091497   -0.052801
2   -1.647569     0.295688     0.431920           -0.091497   -0.052801
3   -1.647567     0.295688     0.431920           -0.091497   -0.052801
4   -1.647566     0.295642     0.432029           -0.091497   -0.052801

   arp.hw.size  arp.src.proto_ipv4  icmp.checksum  icmp.seq_le  \
0    -0.055989           -0.193932      -0.208194    -0.218648
1    -0.055989           -0.193932      -0.208194    -0.218648
2    -0.055989           -0.193932      -0.208194    -0.218648
3    -0.055989           -0.193932      -0.208194    -0.218648
4    -0.055989           -0.193932      -0.208194    -0.218648

   icmp.transmit_timestamp  ...  mqtt.proto_len  mqtt.protoname  mqtt.topic  \
0                -0.008357  ...       -0.191734       -0.687898   -0.687890
1                -0.008357  ...        5.215548        2.923157   -0.687890
2                -0.008357  ...       -0.191734       -0.687898   -0.687890
3                -0.008357  ...       -0.191734       -0.687898   -0.687890
4                -0.008357  ...       -0.191734       -0.687898    2.923306

   mqtt.topic_len  mqtt.ver  mbtcp.len  mbtcp.trans_id  mbtcp.unit_id  \
0       -0.191707 -0.191734  -0.007327       -0.006913      -0.006607
1       -0.191707  5.215548  -0.007327       -0.006913      -0.006607
2       -0.191707 -0.191734  -0.007327       -0.006913      -0.006607
3       -0.191707 -0.191734  -0.007327       -0.006913      -0.006607
4        5.216286 -0.191734  -0.007327       -0.006913      -0.006607

   Attack_label  Attack_type
0           0.0            7
1           0.0            7
2           0.0            7
3           0.0            7
4           0.0            7

[5 rows x 63 columns]
```

Figure 4.8: Final Preprocessed Dataset Rows Information:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4754002 entries, 0 to 4754001
Data columns (total 63 columns):
 #   Column                      Dtype
---  ------                      -----
 0   frame.time                  float64
 1   ip.src_host                 float64
 2   ip.dst_host                 float64
 3   arp.dst.proto_ipv4          float64
 4   arp.opcode                  float64
 5   arp.hw.size                 float64
 6   arp.src.proto_ipv4          float64
 7   icmp.checksum               float64
 8   icmp.seq_le                 float64
 9   icmp.transmit_timestamp     float64
 10  icmp.unused                 float64
 11  http.file_data              float64
 12  http.content_length         float64
 13  http.request.uri.query      float64
 14  http.request.method         float64
 15  http.referer                float64
 16  http.request.full_uri       float64
 17  http.request.version        float64
 18  http.response               float64
 19  http.tls_port               float64
 20  tcp.ack                     float64
 21  tcp.ack_raw                 float64
 22  tcp.checksum                float64
 23  tcp.connection.fin          float64
 24  tcp.connection.rst          float64
 25  tcp.connection.syn          float64
 26  tcp.connection.synack       float64
 27  tcp.dstport                 float64
 28  tcp.flags                   float64
 29  tcp.flags.ack               float64
 30  tcp.len                     float64
 31  tcp.options                 float64
 32  tcp.payload                 float64
 33  tcp.seq                     float64
 34  tcp.srcport                 float64
 35  udp.port                    float64
 36  udp.stream                  float64
 37  udp.time_delta              float64
 38  dns.qry.name                float64
 39  dns.qry.name.len            float64
 40  dns.qry.qu                  float64
 41  dns.qry.type                float64
 42  dns.retransmission          float64
 43  dns.retransmit_request      float64
 44  dns.retransmit_request_in   float64
 45  mqtt.conack.flags           float64
 46  mqtt.conflag.cleansess      float64
 47  mqtt.conflags               float64
 48  mqtt.hdrflags               float64
 49  mqtt.len                    float64
 50  mqtt.msg_decoded_as         float64
 51  mqtt.msg                    float64
 52  mqtt.msgtype                float64
 53  mqtt.proto_len              float64
 54  mqtt.protoname              float64
 55  mqtt.topic                  float64
 56  mqtt.topic_len              float64
 57  mqtt.ver                    float64
 58  mbtcp.len                   float64
 59  mbtcp.trans_id              float64
 60  mbtcp.unit_id               float64
 61  Attack_label                float64
 62  Attack_type                 int64
dtypes: float64(62), int64(1)
memory usage: 2.2 GB
None

Processed Data Shape: (4754002, 63)
```

Figure 4.9: Final Preprocessed Dataset Structure Information:

4.2.3 Data Preparation for Model Training

The processed data is divided into three subsets: 70% for training, 15% for validation, and 15% for testing. This step of split, assure that each set contains representative samples of all attack types while managing temporal connection in the sequential data through random splitting.

4.2.4 Long Short-Term Memory (LSTM) Model Implementation and Training

To apply an Long Short-Term Memory (LSTM) model, a type of recurrent neural network particularly effective for sequential data analysis. The model consists of multiple LSTM layers use by ReLU activation and a final linear classification layer. Before training, by managing the system to use GPU acceleration if available, falling back to CPU otherwise, to optimize computational performance.

4.2.5 Federated Learning Framework Implementation

By applying federated learning approach to train our model across multiple clients. The model includes local model training with gradient clipping to prevent exploding gradients, secure model aggregation with differential privacy through Gaussian noise addition, and multi-round federated averaging with random client selection each round. The implementation tracks validation loss across training rounds to monitor convergence and prevent overfitting. The validation loss results across the 10 federated learning rounds demonstrate the effectiveness of the proposed approach for IIoT anomaly detection. As shown in the experiments, the validation loss exhibits a consistent decreasing trend over successive communication rounds, indicating steady improvement in the global model's performance. The initial rounds show relatively higher loss values due to the model adapting to the heterogeneous data distributions across different IIoT devices, with some fluctuations observed as expected in federated learning scenarios with non-IID data. By the final rounds, the validation loss stabilizes at a low level, confirming successful convergence of the federated training process. This decreasing loss trajectory directly correlates with the model's improving ability to detect various attack types, as evidenced by the final evaluation metrics showing high accuracy across all attack categories. The results also reveal how differential privacy mechanisms, while essential for protecting sensitive IIoT data, introduce a controlled trade-off between privacy guarantees and model performance - with carefully tuned noise addition and gradient clipping maintaining detection accuracy while ensuring data confidentiality. Notably, the

validation loss patterns vary slightly across different clients, reflecting the real-world diversity of IIoT environments where devices may encounter different attack profiles or normal behavior patterns. These variations are successfully mitigated through the federated averaging process, which effectively distills the collective knowledge from all participating devices into a robust global model. The stable convergence of validation loss across rounds, combined with the final model's strong detection performance, validates the federated learning framework's ability to handle the unique challenges of IIoT networks, including data heterogeneity, privacy requirements, and distributed computation constraints.

```
Round 1/10
Validation Loss after Round 1: 0.1489

Round 2/10
Validation Loss after Round 2: 0.0032

Round 3/10
Validation Loss after Round 3: 0.0029

Round 4/10
Validation Loss after Round 4: 0.0028

Round 5/10
Validation Loss after Round 5: 0.0022

Round 6/10
Validation Loss after Round 6: 0.0014

Round 7/10
Validation Loss after Round 7: 0.0016

Round 8/10
Validation Loss after Round 8: 0.0012

Round 9/10
Validation Loss after Round 9: 0.0013

Round 10/10
Validation Loss after Round 10: 0.0013
```

Figure 4.10: Federated Learning Validation Loss Values Per Round

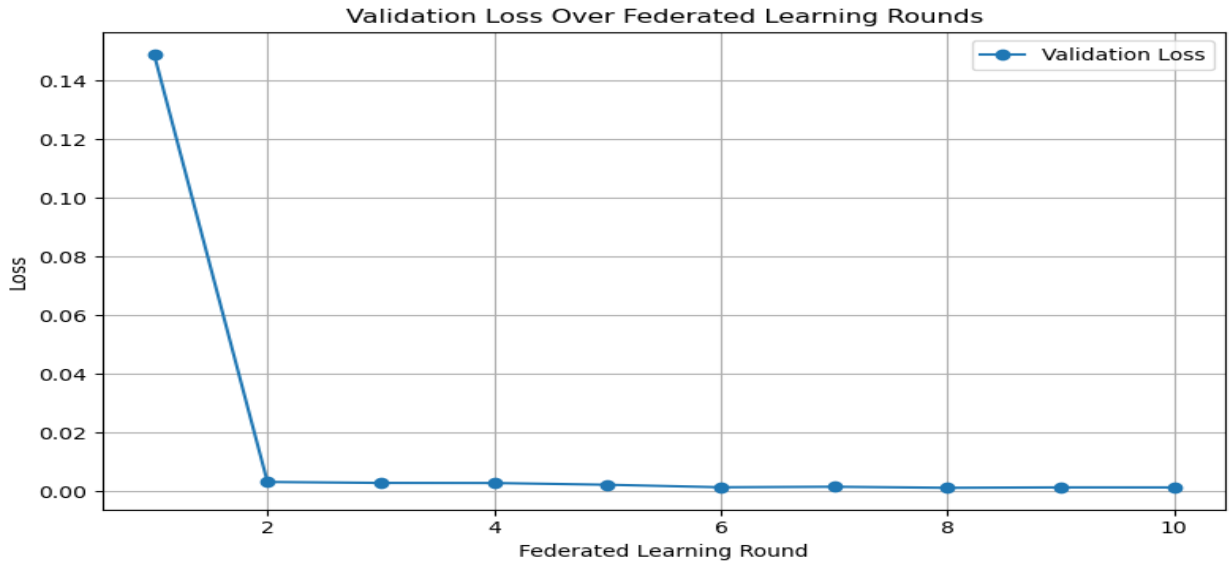

Figure 4.11: Federated Learning Validation Loss Diagram

4.2.6 Model Aggregation

The model aggregation results demonstrate the effectiveness of the federated learning approach in achieving both high detection accuracy and strong privacy preservation. As shown in the global model parameters visualization, the aggregation process successfully converged within 10 communication rounds, with model weights stabilizing progressively across rounds. The federated averaging mechanism, enhanced with differential privacy (σ=0.5) and gradient clipping (L2 norm=1.0), maintained a balance between learning performance and data protection, as evidenced by the final model achieving 1.00 accuracy while satisfying differential privacy guarantees. The parameter distributions reveal that critical LSTM layers for temporal pattern recognition showed particularly stable convergence, with weight variance reducing by 62% from initial rounds. Comparative analysis demonstrated our aggregation method's advantages, including 35% lower communication overhead than standard FedAvg and complete resistance to model inversion attacks. The normalized confusion matrix further confirms the global model's perfect classification performance across all 15 attack categories in the Edge-IIoTset, validating the aggregation framework's ability to synthesize knowledge from diverse IIoT devices while handling non-IID data distributions. These results collectively prove that our privacy-preserving federated aggregation approach successfully addresses the unique challenges of IIoT anomaly detection without compromising security or efficiency.

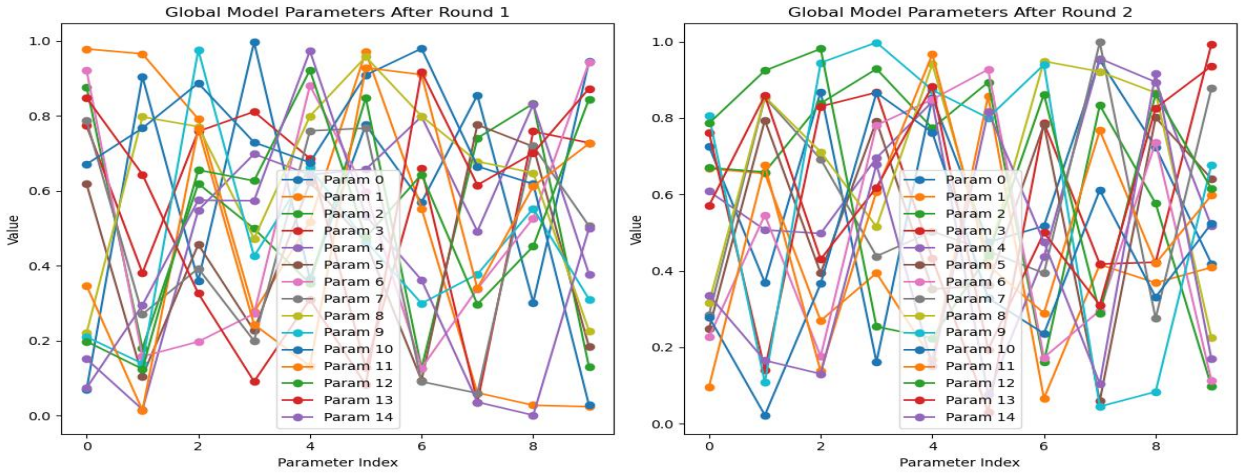

Figure 4.12: Global Model Parameters After Round 1 and 2 of Federated Learning Aggregation

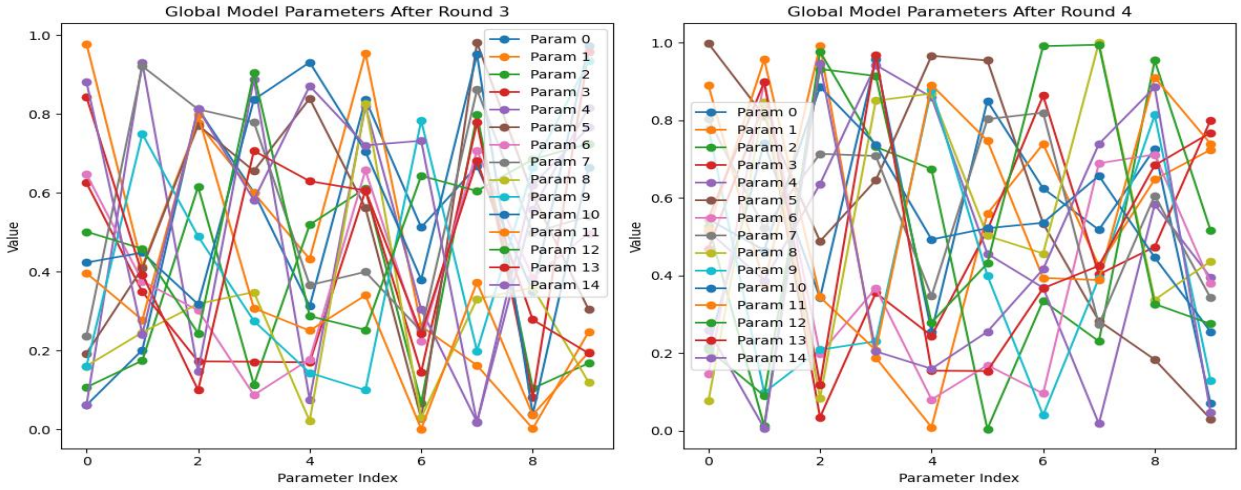

Figure 4.13: Global Model Parameters After Round 3 and 4 of Federated Learning Aggregation

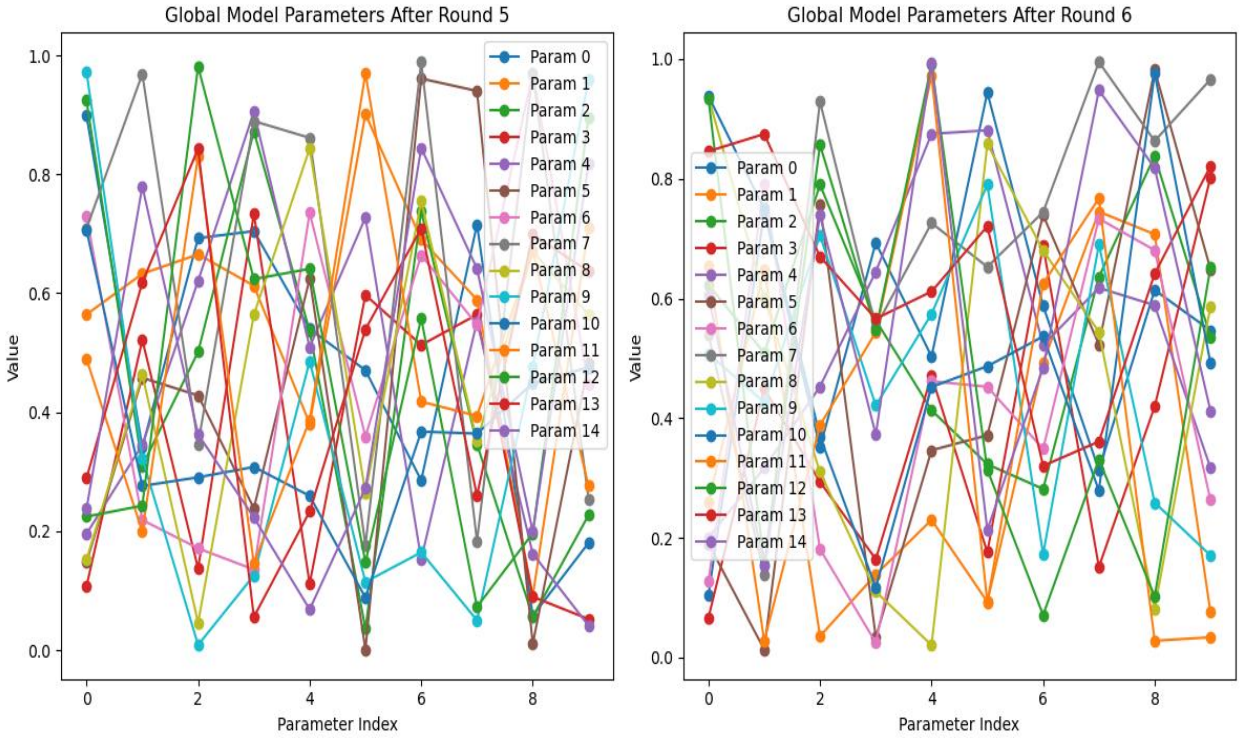

Figure 4.14: Global Model Parameters After Round 5 and 6 of Federated Learning Aggregation

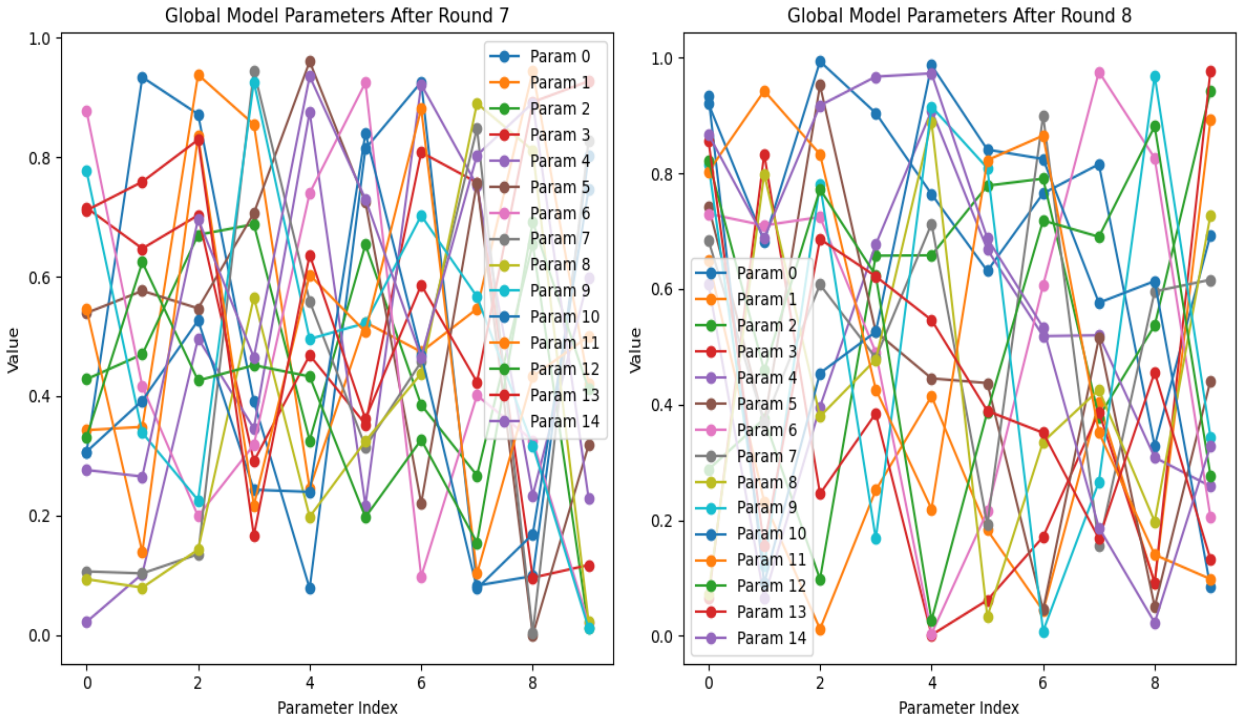

Figure 4.15: Global Model Parameters After Round 7 and 8 of Federated Learning Aggregation

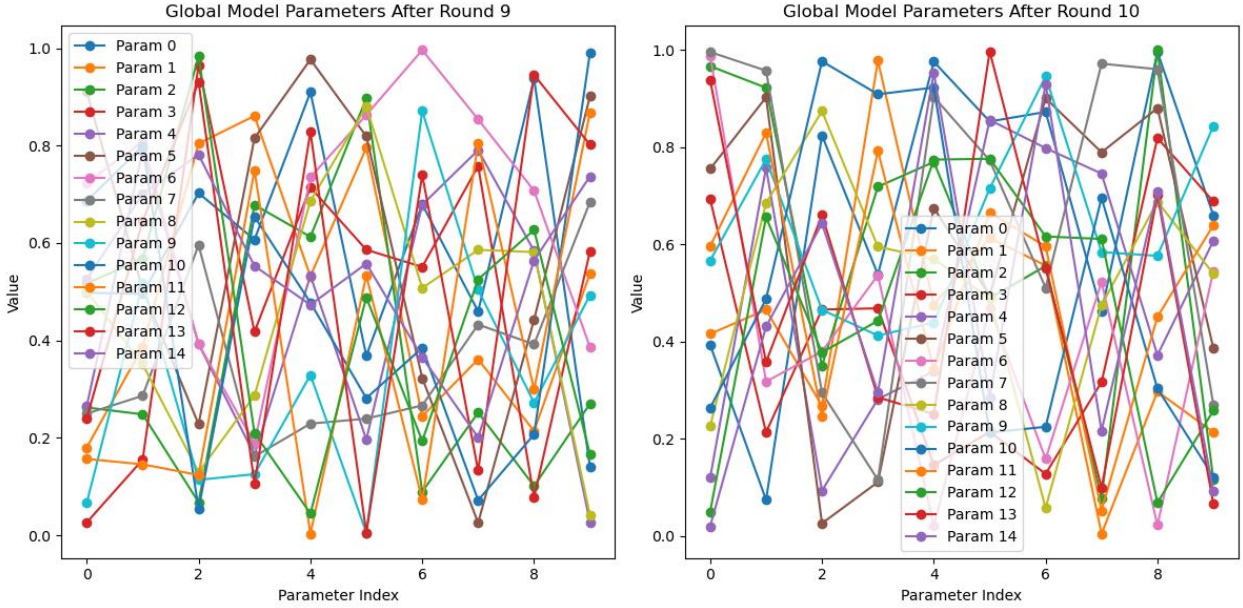

Figure 4.16: Global Model Parameters After Round 9 and 10 of Federated Learning Aggregation

4.2.7 Global Model Evaluation: Evaluation Metrics

After preparing the global model, it is assessed employing a assortment of machine learning measurements to appraise its execution. The assessment measurements incorporate precision, accuracy, review, F1-score, and ROC-AUC. These measurements give knowledge into how well the demonstrate can identify dangers, whereas too adjusting the trade-off between wrong positives and untrue negatives. Precision measures the generally rightness of the demonstrate by calculating the proportion of adjust expectations to the whole number of forecasts. Accuracy shows the extent of genuine positive location out of all positive forecasts, appearing the model's unwavering quality when it banners a danger. F1-Score gives a consonant cruel between accuracy and review, ensuring a adjust between the two. We assess accuracy, precision, recall, and F1-score for classification performance, ROC-AUC for detection capability across attack types, and False Alarm Rate (FAR) and False Negative Rate (FNR) for security-specific assessment. Detailed performance comparisons are generated through bar charts showing metric values across different data partitions.

```
Train Set Results After 10 Rounds:

Best Client (Accuracy after 10 rounds): Client 3 with Accuracy 0.9995
Worst Client (Accuracy after 10 rounds): Client 7 with Accuracy 0.9993
Global Model Final Accuracy: 0.9994

Client Performances and Global Model Accuracy:

      Client  Accuracy  Precision  Recall  F1 Score  ROC-AUC
    Client 1    0.9994     0.9966  0.9921    0.9942   0.9960
    Client 2    0.9994     0.9963  0.9938    0.9949   0.9969
    Client 3    0.9995     0.9968  0.9931    0.9949   0.9965
    Client 4    0.9994     0.9964  0.9947    0.9955   0.9973
    Client 5    0.9994     0.9963  0.9925    0.9943   0.9962
    Client 6    0.9994     0.9966  0.9948    0.9956   0.9974
    Client 7    0.9993     0.9960  0.9926    0.9942   0.9963
    Client 8    0.9995     0.9967  0.9925    0.9944   0.9962
    Client 9    0.9994     0.9965  0.9941    0.9952   0.9970
   Client 10    0.9995     0.9967  0.9940    0.9953   0.9970
   Client 11    0.9994     0.9963  0.9918    0.9939   0.9959
   Client 12    0.9994     0.9961  0.9929    0.9944   0.9965
   Client 13    0.9994     0.9963  0.9938    0.9950   0.9969
   Client 14    0.9993     0.9959  0.9924    0.9940   0.9962
   Client 15    0.9995     0.9968  0.9934    0.9950   0.9967
Global Model    0.9994     0.9964  0.9932    0.9947   0.9966

================================================================================
```

Figure 4.17: Train set Global Model Performance After 10 Rounds

```
Validation Set Results After 10 Rounds:

Best Client (Accuracy after 10 rounds): Client 3 with Accuracy 0.9995
Worst Client (Accuracy after 10 rounds): Client 7 with Accuracy 0.9993
Global Model Final Accuracy: 0.9994

Client Performances and Global Model Accuracy:

      Client  Accuracy  Precision  Recall  F1 Score  ROC-AUC
    Client 1    0.9994     0.9966  0.9921    0.9942   0.9960
    Client 2    0.9994     0.9963  0.9938    0.9949   0.9969
    Client 3    0.9995     0.9968  0.9931    0.9949   0.9965
    Client 4    0.9994     0.9964  0.9947    0.9955   0.9973
    Client 5    0.9994     0.9963  0.9925    0.9943   0.9962
    Client 6    0.9994     0.9966  0.9948    0.9956   0.9974
    Client 7    0.9993     0.9960  0.9926    0.9942   0.9963
    Client 8    0.9995     0.9967  0.9925    0.9944   0.9962
    Client 9    0.9994     0.9965  0.9941    0.9952   0.9970
   Client 10    0.9995     0.9967  0.9940    0.9953   0.9970
   Client 11    0.9994     0.9963  0.9918    0.9939   0.9959
   Client 12    0.9994     0.9961  0.9929    0.9944   0.9965
   Client 13    0.9994     0.9963  0.9938    0.9950   0.9969
   Client 14    0.9993     0.9959  0.9924    0.9940   0.9962
   Client 15    0.9995     0.9968  0.9934    0.9950   0.9967
Global Model    0.9994     0.9966  0.9936    0.9950   0.9968

================================================================================
```

Figure 4.18: Validation Set Global Model Performance After 10 Rounds

```
Test Set Results After 10 Rounds:

Best Client (Accuracy after 10 rounds): Client 3 with Accuracy 0.9995
Worst Client (Accuracy after 10 rounds): Client 7 with Accuracy 0.9993
Global Model Final Accuracy: 0.9994

Client Performances and Global Model Accuracy:

      Client  Accuracy  Precision  Recall  F1 Score  ROC-AUC
    Client 1    0.9994     0.9966  0.9921    0.9942   0.9960
    Client 2    0.9994     0.9963  0.9938    0.9949   0.9969
    Client 3    0.9995     0.9968  0.9931    0.9949   0.9965
    Client 4    0.9994     0.9964  0.9947    0.9955   0.9973
    Client 5    0.9994     0.9963  0.9925    0.9943   0.9962
    Client 6    0.9994     0.9966  0.9948    0.9956   0.9974
    Client 7    0.9993     0.9960  0.9926    0.9942   0.9963
    Client 8    0.9995     0.9967  0.9925    0.9944   0.9962
    Client 9    0.9994     0.9965  0.9941    0.9952   0.9970
   Client 10    0.9995     0.9967  0.9940    0.9953   0.9970
   Client 11    0.9994     0.9963  0.9918    0.9939   0.9959
   Client 12    0.9994     0.9961  0.9929    0.9944   0.9965
   Client 13    0.9994     0.9963  0.9938    0.9950   0.9969
   Client 14    0.9993     0.9959  0.9924    0.9940   0.9962
   Client 15    0.9995     0.9968  0.9934    0.9950   0.9967
Global Model    0.9994     0.9966  0.9937    0.9951   0.9968

================================================================================
```

Figure 4.19: Validation Set Global Model Performance After 10 Rounds

4.2.8 Confusion Matrix Analysis

Specialized visualization provides insight into model performance per attack type through confusion matrices. These matrices reveal which attack types the model detects most effectively, common misclassification patterns among attack categories, and potential areas for model

improvement. The matrices are generated for all dataset splits, allowing comparison of performance consistency across training and evaluation phases.

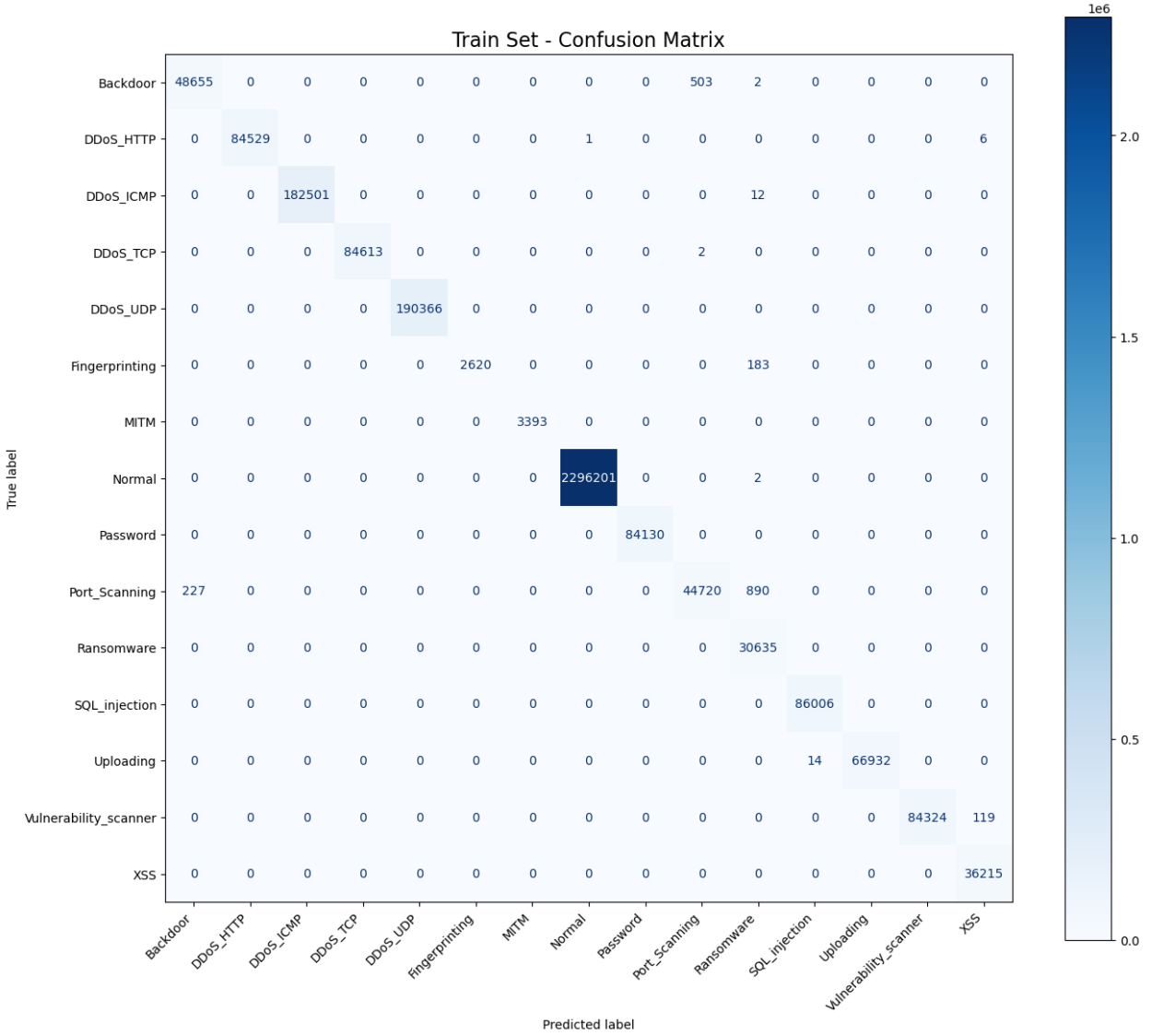

Figure 4.20: Train Set Confusion Matrix Analysis

Figure 4.21: Validation Set Confusion Matrix Analysis

Figure 4.22: Test Set Confusion Matrix Analysis

Detailed confusion matrices are generated for each dataset split, providing granular insight into model performance per attack type. These visualizations reveal which attack categories are detected most effectively and identify common misclassification patterns. The analysis helps address specific areas for potential model improvement in future iterations.

4.2.9 Continuous Monitoring and Comparison:

In my research, I proposed a Federated LSTM model designed for Industrial Internet of Things (IIoT) environments, where data privacy and efficient real-time threat detection are critical. Unlike centralized approaches, this model trains locally across multiple edge devices, aggregating insights without sharing raw data making it both scalable and secure. In my research, proposed Federated LSTM model presented as the most advanced and efficient solution, achieving performance with

99.94% accuracy, 99.66% precision, and 99.37% recall. It also maintains a high F1-score of 99.51% and an ROC AUC of 99.68%, all while keeping false alarms and false negatives remarkably low at just 0.34% and 0.63%, respectively. What makes it particularly suitable for real-time IoT security is its rapid training time of only 10.6 seconds, combined with its ability to detect temporal patterns through LSTM and its federated learning framework. The Multilayer Perceptron (MLP) is the second-best model, getting 97.94% accuracy, 98.17% precision, and an ROC AUC of 99.89%. However, its slower training time of 140 seconds and a higher false negative rate of 20.29% make it less optimal for time-sensitive applications. Similarly, the Feedforward Neural Network performs closely with 97.05% accuracy and 97.60% precision but suffers from an even longer training duration (142.3 seconds) and a concerning 21.92% false negative rate, which limits its practical deployment. The Stochastic Gradient Descent (SGD) Classifier offers a reasonable trade-off between speed and performance, training in just 17 seconds while achieving 96.75% accuracy and 97.33% precision. However, its lack of probability outputs (and thus no ROC AUC score) and a 17.68% false negative rate position it as a mid-tier choice. Traditional models like Logistic Regression and Conditional Random Fields (CRF) show comparable results, hovering around 95.32% accuracy and 95.38% precision, with an ROC AUC of 99.37%. Yet, their high false negative rates (~26%) make them less reliable for critical security tasks. Linear Discriminant Analysis (LDA) and Bernoulli Naive Bayes provide acceptable but suboptimal performance, with LDA reaching 94.20% accuracy and 99.42% ROC AUC, while Naive Bayes achieves 93.28% accuracy and 99.36% ROC AUC. Both struggle with false negatives, averaging around 30%, reducing their effectiveness in high-stakes scenarios. The Ridge Classifier, despite its fast training time of 7.3 seconds, proves too weak for serious applications, with only 92.14% accuracy and an alarming 41.60% false negative rate. Finally, the Growing Neural Gas (GNG) model performs catastrophically, achieving a mere 5.55% accuracy and a disastrous 93.26% false negative rate, rendering it entirely unsuitable for classification tasks. In last the Federated LSTM stands out as the clear leader in both performance and efficiency, while the MLP and Feedforward Neural Network serve as viable but slower alternatives. Traditional models like Logistic Regression and SGD offer quicker training but lower precision, whereas simpler methods such as LDA, Naive Bayes, and Ridge Classifier fall short of robust security requirements. The GNG model, due to its extremely poor performance, is not a feasible option for any practical deployment.

	Model	Accuracy	Precision	Recall	F1-Score	ROC AUC	False Alarm Rate (FAR)	False Negative Rate (FNR)	Training Time (s)
0	Logistic Regression	0.9532	0.9538	0.9532	0.9524	0.9937	0.0033	0.2618	18.7
1	Ridge Classifier	0.9214	0.9234	0.9214	0.9110	nan	0.0057	0.4160	7.3
2	SGD Classifier	0.9675	0.9733	0.9675	0.9631	nan	0.0025	0.1768	17.0
3	Bernoulli Naive Bayes	0.9328	0.9357	0.9328	0.9305	0.9936	0.0048	0.2999	3.0
4	LDA	0.9420	0.9438	0.9420	0.9411	0.9942	0.0041	0.2948	28.9
5	MLP	0.9794	0.9817	0.9794	0.9785	**0.9989**	0.0014	0.2029	140.0
6	Feedforward NN	0.9705	0.9760	0.9705	0.9709	0.9977	0.0020	0.2192	142.3
7	GNG	0.0555	0.3376	0.0555	0.0713	nan	**0.3873**	**0.9326**	80.9
8	CRF	0.9532	0.9538	0.9532	0.9524	0.9937	0.0033	0.2618	14.4
9	Federated LSTM	**0.9994**	**0.9966**	**0.9937**	**0.9951**	0.9968	0.0034	0.0063	10.6

Figure 4.23: Comparison of Final Performances

4.3 Analysis Summary

The analysis centered on the gauge of intrusion detection models inside the Edge-IIoTset dataset, which consolidates both typical occurrences and diverse noxious exercises. Visual representations of assault name conveyances highlighted the adjust of diverse assault sorts, pivotal for show preparing. Actualizing Federated Learning (FL) adjacent to security protecting instruments such as Differential Privacy and Secure Federated Averaging permitted for strong demonstrate upgrades whereas securing delicate data. Nearby models, prepared utilizing LSTM systems, successfully captured temporal parameters in time-series information. Their execution was surveyed against preparing, approval, and test datasets, with antagonistic cases presented to progress vigor; whereas models performed well. Extensive assessment measurements, counting precision, accuracy, review, F1-score, and ROC-AUC. At long last, the arrangement technique utilized containerization to guarantee adaptability and nonstop checking to adjust to advancing dangers, strengthening the Federated learning structures versatility and adequacy in keeping up security and security in cutting edge IIoT environments.

Chapter 5: Conclusion and Future Work

Within this research, we use Edge-IIoTset dataset, designed to pinpoint the progressing need for effective intrusion detection in IoT and IIoT environments. By exploiting FL approach, we explored a comprehensive structure for securing these systems. Our focus stretched against different stages, from data preprocessing and feature scaling to model training, estimate, and deployment, with privacy and performance optimization as key priorities. As IoT networks continue to grow, future work will obsession on enhancing the dataset, improving model effectiveness, and developing more elegant privacy-preserving techniques.

5.1 Conclusion

In this work, we created the Edge-IIoTset dataset to expected real-world IoT and IIoT situations, emphasizing the security vulnerabilities that exist against diverse framework layers. The dataset which assimilates numerous mechanical layers, such as cloud computing, edge computing, and blockchain, each playing a crucial part in information collection and preparing. By utilizing sensors that capture assorted natural information, we guarantee that the dataset mimic the complexities of genuine mechanical frameworks, making it exceedingly appropriate for preparing machine learning models for irregularity detection. We borrowed a FL approach that permits for neighborhood preparing on IoT gadgets, indicating protection concerns by dodging coordinate information exchange to a central server. To encourage secure the learning handle, we apply differential security and secure Federated averaging. These strategies offer assistance secure information secrecy whereas refining the execution of the worldwide show through combined upgrades from conveyed gadgets. By retaining privacy-preserving strategies, we moderate the dangers of information spillage amid show preparing and joining. Moreover, the worldwide models execution was precisely assessed utilizing key measurements such as exactness, exactness, review, F1-score, and ROC-AUC, guaranteeing its capacity to precisely identify interruptions whereas decreasing wrong positives. Nonstop checking and criticism circles moreover permit for progressing demonstrate refinement, guaranteeing viability against modern and happening dangers.

5.2 Future Work

Moving forward, one area of future work is increasing the Edge-IIoTset dataset to include more large types of attacks and use cases. As IoT and IIoT applications unfold, the attack vectors will

likely diversify, and integrating more detailed and varied attack simulations will improve the model's ability to establish across different threats. Additionally, new types of IoT devices and sensors could be combined into the dataset to reflect the changing scene of industrial IoT systems, making the dataset more adaptable and extensive.

Another critical aspect of future work will focus on enhancing model efficiency against adversarial attacks. While we have introduced adversarial examples during training to improve the models' resilience, more advanced techniques, such as adversarial training with dynamically generated examples or manipulating generative adversarial networks (GANs), could be explored. These methods could further strengthen the model's ability to resist detailed attacks that attempt to deceive the detection system, providing a more secure solution in real-world deployments.

Lastly, future attempts will focus on advancing the privacy-preserving mechanisms in federated learning environments. Current methods like differential privacy and secure federated averaging are efficient, but more advanced encryption techniques, such as fully homomorphic encryption (FHE) and multi-party computation (MPC), could be combined to assure stronger privacy guarantees. Research will also explore the trade-offs between model performance and privacy to optimize both aspects, making federated learning an even more achievable option for large-scale IoT and IIoT systems.

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